ADAPTIVE TRAFFIC CONTROL EFFECT ON ARTERIAL TRAVEL TIME CHARACTERISTICS

A Dissertation
Presented to
The Academic Faculty

By

Seung Kook Wu

In Partial Fulfillment
Of the Requirement for the Degree
Doctor of Philosophy in Civil Engineering

Georgia Institute of Technology

December 2009

ADAPTIVE TRAFFIC CONTROL EFFECT ON ARTERIAL TRAVEL TIME CHARACTERISTICS

Approved by:

Dr. Michael Hunter, Advisor
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Michael Rodgers
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Randall Guensler
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Roshan J. Vengazhiyil
School of Industrial and Systems Engineering
Georgia Institute of Technology

Dr. John Leonard
School of Civil and Environmental Engineering
Georgia Institute of Technology

Date Approved: October 29, 2009

ACKNOWLEDGEMENTS

I would like to thank my thesis advisory committee members, Dr. Hunter, Dr. Rodgers, Dr. Leonard, Dr. Guensler, and Dr. Vengazhiyil for their invaluable support and encouragement throughout my doctoral study. My deepest gratitude and appreciation are given to my advisor, Dr. Hunter. His enthusiasm, insight, and patience provided a guide without which I would not be where I am.

Many thanks are also owed to my current and former colleagues, Wonho, Hoe Kyoung, Saroch, Yooshik, Lakshmi, Guin, Danju, Dwayne, Matt, Seungho, Hosung, Mihyun, Joonho, Jungwook, Seungjoo, and Dongha. They helped my research and life.

I would also like to give special thanks to Shafi, Adria, Helen, and Jim. Their warmest help got me through hard times on my spiritual journey.

And finally, I am grateful for being son of my parents, husband and friend of my wife Heejung, and father of my son Hyunsoo. By the being, my life is supported.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
ACS-Lite	Adaptive Control Software Lite
ACTRA	Traffic control server software developed by SIEMENS
CDF	Cumulative Distribution Function
DMI	Distance Measuring Instrument
DOT	Department of Transportation
FHWA	Federal Highway of Administration
GPS	Global Positioning System
HDOP	Horizontal Dilution of Precision
ISTEA	Intermodal Surface Transportation Efficiency Act
ITE	Institute of Transportation Engineers
ITS	Intelligent Transportation System
LOS	Level of Service
MLE	Maximum Likelihood Estimation
MOE	Measure of Effectiveness
NCHRP	National Cooperative Highways Research Program
O-D	Origin and Destination
OPAC	Optimization Policies for Adaptive Control
PDA	Personal Digital Assistant
RPART	Recursive PARTitioning
SAFETY-LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users
SCATS	Sydney Coordinated Adaptive Traffic System
SCOOT	Split Cycle Offset Optimization Technique
SHRP II	Strategic Highway Research Program II
TEA-21	Transportation Equity Act for the 21st Century
TRB	Transportation Research Board
TRIPTI	Travel Run Intersection Passing Time Identification

SUMMARY

An arterial traffic control system influences the travel time characteristics of a corridor, including the average corridor travel time and the travel time reliability. However, reliability measures have typically been outside of the focus of arterial control system performance evaluation studies. To assess the effectiveness of arterial traffic control performance evaluation studies are normally limited to average measures of travel time, speed, or delay. As an advanced traffic management system, adaptive traffic control has been developed to address real time demand variability. Thus, an evaluation of the adaptive traffic control system based on reliability may be as important as evaluation based on average travel time or delay.

In addition, arterial control systems may also affect the performance of side street traffic as well as arterial corridor traffic. The performance of side street traffic is another measure that should be used in the assessment of the effectiveness of any arterial traffic control system. Finally, an arterial's operational performance often changes throughout a day and over the arterial length. Thus, a system-wide measure that reflects the range of observed operations is needed to thoroughly assess the performance.

Given these issues the goal of this research is the development of procedures to evaluate adaptive traffic control's effect on arterial characteristics such as travel time distribution, reliability, side street performance, and system-wide performance. The developed procedures were applied to the evaluation of an adaptive traffic control system, SCATS (Sydney Coordinated Adaptive Traffic System) in Cobb County, Georgia, that replaced a semi-actuated coordinated control system.

After the procedures were applied, it was found that SCATS produced a less extreme shape of travel time distribution, possibly due to the adaptive feature, but that it did not make statistically significant changes in the selected overall analysis measures. Also, it was found that the results of the performance evaluation can vary depending on the measures selected or the study period and location.

CHAPTER 1. INTRODUCTION

Background

Urban street congestion is one of the major problems in most metropolitan areas. It is reported in the Urban Mobility Report 2007 that congestion levels in 85 largest metropolitan areas in The United States have grown continuously and that the economic loss from roadway congestion in 2005 alone amounted to more than $78 billion *(1)*. In an effort to address urban congestion federal funding has been steadily increasing, from ISTEA (1991~1997), to TEA-21 (1998-2003), and currently SAFETY-LU (2005-2009), through the Congestion Mitigation and Air Quality Improvement Program and the Congestion Relief Program *(2-4)*. Many states and local governments also have congestion management programs. These combined efforts have funded various advanced traffic management and adaptive control systems as part of their attempt to relieve arterial congestion. A primary objective of this research is developing metrics that may be utilized to measure the effect of these advanced control systems on arterial travel time reliability.

Congestion affects a transportation system in two ways; it increases travel time and reduces reliability *(5, 6)*. From a transportation perspective, reliability may be defined as the level of travel time variation, or the probability that travelers will arrive at their destination within a given time. Reliable transportation facility help travelers better predict and schedule their trips by providing low travel time variability and requiring travelers to allot only small buffer times to ensure on time arrival. As such, travel time reliability is considered as a key transportation service performance measure by road users and related agencies. For instance, a road user survey in Baltimore found that for work trips in an ideal transportation system that travel time reliability is the 2nd most important factor, following vehicle reliability *(7)*. The importance of travel time reliability is becoming more pronounced as many manufacturers adopt just-in-time manufacturing process *(8)*. This importance is well recognized at the federal, state and local levels. For example, the Federal Highway Administration has been monitoring mobility indices on freeways in selected urban metropolitan areas through the Mobility Monitoring Program since 2001, with travel time reliability measures among the key variables monitored *(9)*. A number of state DOTs also monitor travel time reliability in an effort to provide travelers information and measure transportation service performance. More recently, the Strategic Highway Research Program II authorized in the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETY–LU) includes reliability as one of the research focus areas *(10)*.

A key factor affecting an arterial's operation is the traffic control. The typical goal of traffic control algorithms is the minimization of average delay, or the number of stops, through the adjustment of signal control parameters such as phase length, cycle length, and offset *(11)*. However, individual vehicle delays or travel times are sometimes highly variable due to the interaction between the control, short term traffic demand variation, and vehicle arrival patterns. The importance of signal control and traffic demand variation as significant sources of reliability reductions has been identified by Federal Highway Administration and Transportation Research Board *(5, 6)*. As adaptive traffic control attempts to maximize the signal control effectiveness by responding to real time traffic conditions *(12)* it is reasonable to inquire if it may also provide reliability improvements over traditional time of day control.

Another arterial characteristic that may be affected by adaptive traffic control systems is the performance of the traffic originating from intersecting side (minor) streets. The most common arterial control system is semi-actuated coordinated control. The primary goal of such a system is most often serving the through movement on the arterial (typically facilitated through the use of a fixed background cycle), with the serving of the side street travel of secondary importance. However, many adaptive traffic control algorithms monitor traffic conditions on both the major street and intersecting side streets on a real-time basis, attempting to provide control parameters that best serve all movements.

Problem identification

Current research on reliability is primarily limited to freeway operation surveillance data drawn from congestion monitoring and ATIS applications. Although arterial systems are included in most origin destination paths of travelers, arterial reliability issues have not been actively covered. This study identified several issues that existing research efforts have not fully explored.

Firstly, two control systems on an arterial could achieve the same average travel time yet have different levels of reliability. A potential example of such an occurrence is shown in the travel time boxplots below (Figure 1). These boxplots are based on travel time data collected over a 2.5 mile stretch of Cobb Parkway in Cobb County, Georgia. The left and right graph show travel time boxplots when the arterial was under time-of-day based semi-actuated coordinated control and right graph shows and SCATS (Sydney Coordinated Adaptive Traffic System) control, respectively. Except for the morning peak period, these two graphs show similar average travel times. However, the travel time variation is consistently different between the control types. This may suggest that travel time reliability captures arterial performance behaviors not reflected in average travel time and may describe an arterial's quality of service from a different perspective.

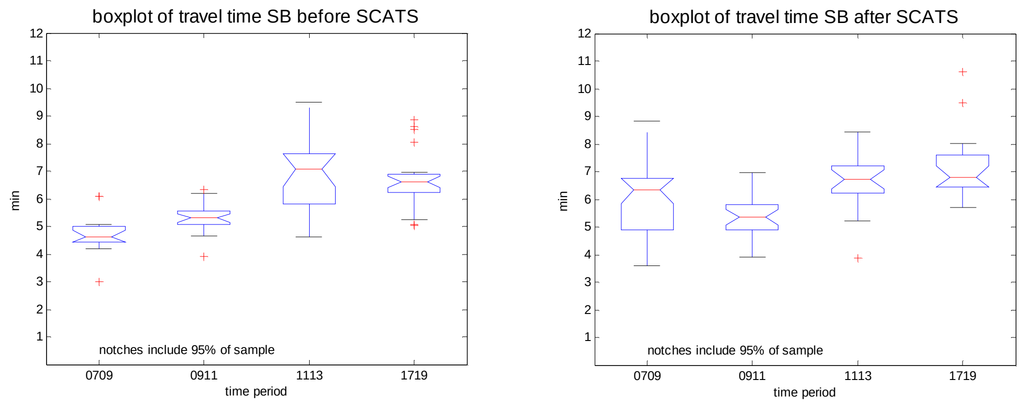


Figure 1: Average and variability of observed travel times over time of day

As seen, arterial control may affect arterial travel time reliability, however, reliability measures have typically been outside of the focus of arterial control system performance evaluation studies. To assess the effectiveness of arterial traffic control, often to justify the investment, traffic control system performance evaluation studies are normally limited to average measures of travel time, speed, or delay. As an advanced traffic management system, adaptive traffic control has been developed to address real time demand variability. Thus, an evaluation of the adaptive traffic control system based on reliability may be as important as evaluation based on average travel time or delay.

Secondly, arterial control systems affect the performance of side street traffic as well as arterial corridor traffic. However, the spatial scope of most previous arterial evaluation studies has been limited to through traffic or individual side street delays. The aggregate performance of side street traffic is another measure that should be used in the assessment of the effectiveness of any arterial traffic control system.

Finally, an arterial's operational performance often changes throughout a day and over the arterial length. Thus, a system-side measure that reflects the range of observed operation is needed to thoroughly assess the performance.

Study objectives

Given the problems identified in the previous section, the goal of this research is the development of procedures to evaluate adaptive traffic control's effect on arterial characteristics such as travel time reliability, side street performance, and system-wide performance. The developed procedures will be applied to the evaluation of an adaptive traffic control system, SCATS (Sydney Coordinated Adaptive Traffic System) in Cobb County, Georgia that replaced a semi-actuated coordinated control, referred to as ACTRA. In order to achieve this goal, the following objectives are established.

- Develop field data collection and reduction procedure.
- Investigate arterial travel time distributions.
- Develop a procedure to evaluate a control system based on reliability measures.
- Develop a procedure to evaluate side street traffic performance under compared systems.
- Develop a system-wide measure for an arterial network.

Expected contributions

After the objectives of the study are achieved, the following contributions are expected.

- The development of an arterial travel time data collection and analysis procedure using vehicle trajectory data.
- The development of a data collection method to capture side street traffic performance.
- Gaining an understanding of travel time distribution under adaptive traffic control.
- The outline of reliability measure characteristics suitable for arterial control.
- The development of a non-parametric method for statistical test of the effect of control on congestion measures.
- The development of a procedure to quantify side street traffic performance.
- Application of two-fluid theory to trip time versus stop time relationship for measuring system-wide performance of an arterial network.

Study scope

The study area is located in southeast portion of Cobb County and includes fifteen intersections on three arterials: Atlanta Road, Paces Ferry Road, and Cumberland Parkway. The travel time data were collected using GPS test vehicles. ACTRA data collection was conducted from November 9, 2004 to December 8, 2004, and SCATS data collection was from April 12, 2005 to May 15, 2005. No data was collected during the week of, or the weekends adjacent to, the Thanksgiving holiday. Also the data collection was conducted under clear weather and non-incident conditions. It is recognized that this field data does not capture adaptive traffic benefits that could be realized under incident or non-recurrent congestion conditions. A potential research approach to determine such effects is discussed as future work in the conclusion chapter.

Chapter outline

Chapter 2 summarizes the previous arterial traffic control system evaluation studies, reliability experienced by road users, existing definitions and measures of reliability, programs for monitoring and use of reliability measures, and reliability trends in the U.S. and Atlanta region in which the study site is located. Chapter 3 describes the study area and data collection and reduction procedure. Chapter 4 examines travel time distributions under the compared control systems based on end-to-end route data. The findings are related to performance measures. Chapter 5 reviews existing reliability measures and evaluates the performance of the control systems based on the developed statistical procedure. End-to-end route data are also used in this analysis. Chapter 6 evaluates side street originating traffic performance and compares it with end-to-end route travel time based results from the previous chapter. Chapter 7 applies the two-fluid theory to the collected data and attempts to find a system-wide performance measure. Chapter 8 summarizes the findings from the analysis chapters. Finally, contributions and future research are discussed.

Chapter 2. LITERATURE REVIEW

This chapter discusses a general feature of semi-actuated coordinated control and SCATS. Then, summaries of reliability experienced by road users, existing definitions and measures of reliability in transportation, programs for monitoring and use of reliability measures, and reliability trends in the U.S. and Atlanta region are presented. Also, previous arterial traffic control system evaluation studies are reviewed. Lastly, the reason why reliability is important for the evaluation of adaptive traffic control is provided. Studies on arterial travel time distribution, two-fluid theory, and adopted statistical methods are reviewed in the corresponding chapters.

General feature of semi-actuated coordinated control and SCATS

Semi-actuated coordinated signal control is used where minor side streets intersect with a major arterial or a collector with the goal to facilitate the movement on the major corridor *(13)*. Detectors are located on the side street approaches and the green stays on the major street unless a detector call is noted on the side streets. With a fixed background cycle, the side street green time can be limited so that it does not interfere with the progression along the coordinated intersections. The control parameters and the duration time are pre-determined by an off-line signal timing study and typically they are set to maximize the width of the green-band or to minimize a performance index, such as overall delays or the number of stops *(11)*. In contrast to the pre-timed semi-actuated coordinated control, SCATS adjusts the control parameters responding to real time detector information.

SCATS subdivides the system into small subgroups of intersections *(13)*. The underlying strategy is to maintain an equal degree of saturation on important approaches at the critical intersection in a subgroup. This is accomplished by setting the green time such that it is just long enough to pass the platoon of vehicles waiting *(14)*. The cycle length is set to maintain a degree of saturation of approximately 0.9 at the most heavily used approaches. Coordination of multiple subgroups can be obtained by linking subgroups with a common cycle time *(14)*. An Offset value is selected for a subgroup and when multiple subgroups are combined, the linking offset is determined to facilitate the flow of the heavier volume group *(14)*.

Reliability experienced by road users

On a congested road, traffic conditions are unreliable and higher than average travel times can be observed. In Figure 2, weekday travel times on 12 mile segment of SR520 in Seattle, Washington from January to April 2003 are presented *(5)*. The average travel time is 12 minutes but in severe congestion conditions, it increases to as much as 25 minutes. Road users who plan to use this road should consider this variability in travel time in selecting a departure time that will allow an on time arrival at their destination. This is a good example of how travel time reliability affects a traveler's trip plan. For several decades, travel time reliability has been considered as one of the most important performance measures by road users and transportation professionals. In 1966, in a study conducted by researchers at the University of Maryland road users were interviewed to find attributes of an ideal transportation service. It was found that travel time reliability was ranked as the second most important attribute for work trips, following vehicle reliability *(7)*. In 1974, a survey of opinions from transportation planners and engineers found that the most important attribute for modal choice is travel time reliability, followed by safety and travel time *(15)*.

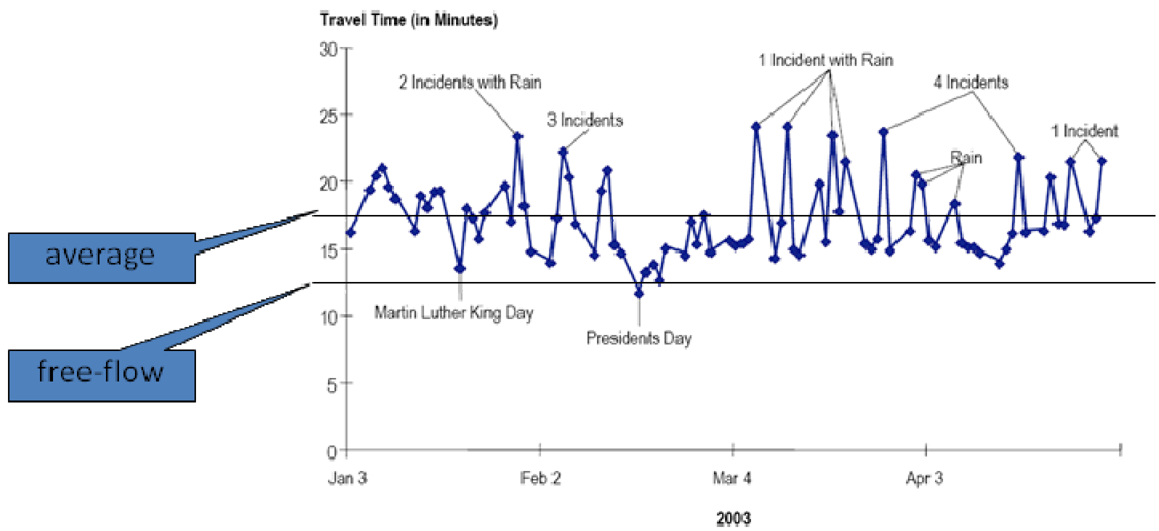


Figure 2: Weekday travel time on SR520 Seattle
Source *(5)*

A stated preference survey in 1995 (Table 1) showed that road users consider reliability of travel time as important as mean travel time when selecting travel routes *(16)*. The importance of travel time reliability has been captured quantitatively in modeling efforts to that sought to determine the value of time and value of reliability. Those studies found that monetary value of travel time reliability ranges from one to two times as high as that of travel time *(8, 17-19)*.

Table 1: Stated preference survey on routes of different mean and standard deviation of travel time

Case	Route	Route description	Mean time	Standard Deviation	Stated choice
1	1	30min every day	30	0	310
	2	20min 4days/week 40min 1day/week	24	8.94	254
2	1	30min every day	30	0	476
	2	20min 4days/week 60min 1day/week	28	17.89	88
3	1	30min every day	30	0	159
	2	20min 3days/week 30min 2day/week	24	5.48	405
4	1	30min every day	30	0	454
	2	20min 3days/week 45min 2day/week	30	13.69	110
5	1	30min every day	30	0	496
	2	20min every day 120min 1day/2week	30	33.54	68

Definition of reliability

In reliability engineering, reliability is defined as the probability that a product or service will operate properly for a specified period time under design operating conditions without failure *(20)*. In transportation engineering, since reliability is one of the recently evolving performance measures, no common definition exists *(21)*. Instead, different studies have tended to develop their own unique definitions of reliability. However, most definitions in the literature address transportation service consistency over time and on-time arrival predictability. It is noted that the terms "reliability" and "travel time reliability" are used interchangeably in transportation literature to address the consistency in travel time. Table 2 summarizes the intent of the reliability measures in the literature.

Table 2: Reliability in transportation engineering

Purpose of reliability measure	Source
Captures the level of consistency in transportation service (e.g., hour to hour and day to day).	*(22)*
Describes the transportation service consistency for a mode, trip, route, or corridor for a time period viewed by travelers in relation to their experience.	*(23)*
Defined as travel time variability from one day to the next.	*(5)*
Reflects the ability of a system to perform its intended function accurately, consistently, and safely over time. This may represent the likelihood of on-time arrival, the consistency of the travel time for the trip under consideration, as well as the deviation of the actual travel time from the expected or scheduled travel time.	*(24)*
Represents the ability of travelers to predict travel time for a trip and to arrive at destination within an on-time window.	*(25)*
Defined as the probability that traffic can reach a given destination within a stated time.	*(26)*
Measure of transportation service consistency.	*(6)*
The level of variation between the expected travel time (based on schedule or average travel time) and actual travel time.	*(27)*
Reflects the percentage of travel that falls within certain bounds of the expected travel time.	*(28)*
Percent of on-time performance for a given time schedule.	*(27)*
Probability of arriving at destination within the expected time or schedule.	*(29)*
How well conditions on a corridor satisfy travelers' expectations regarding travel time.	*(30)*
The range of travel times experienced during a large number of daily trips.	*(30)*
The impact of non-recurrent congestion on the transportation systems estimated as the variation in the duration, extent, and intensity of congestion on a system.	*(31)*
The consistency or dependability in travel times as measured from day-to-day and/or across different times of day.	*(32)*

Existing reliability measures

Reliability measures developed or suggested by previous studies are summarized.

Researchers at the Texas Transportation Institute and Cambridge Systematics categorized reliability measures into three groups: statistical range measure, buffer measure, and tardy trip indicator *(23)*. The existing measures are summarized into statistical range measures, buffer measures, and tardy trip indicators.

Statistical range measures

These measures attempt to capture the size of the variation of travel time typically by incorporating sample standard deviation into the measure. The measures under this category are familiar to statisticians and engineers but may be difficult to explain to the general public.

- Travel time window (*(23, 31)*)

  The mathematical expression of this measure is average travel time $\pm$ standard deviation. The percentage of trips included in this window depends on the underlying travel time distribution. Under the normal distribution assumption, 68% of trips are accounted for by this measure.

- Percent variation (*(23)*)

  This measure is a percentage expression of coefficient of variation. Since this measure is a normalized standard deviation of travel time by average travel time, it gives a better picture when facilities of different lengths are presented together or compared. The mathematical expression is (standard deviation of travel time)/(average travel time) $\times$ 100.

- Variability index (*(23, 30)*)

  This index is a ratio of 95% confidence interval of peak travel time to 95% confidence interval of off-peak travel time.

- Polus' reliability measure of arterial (*(33)*)

Polus used reciprocal of standard deviation of travel time to measure arterial reliability. By utilizing the reciprocal of standard deviation the reliability measure increase as the reliability improves, i.e. the standard deviation decreases.

- Range of travel time (*(30)*)

  The mathematical form is similar to travel time window. The difference is that it contains 85% of trips if assuming normal distribution. It is calculated by average travel time $\pm 1.44 \times$ standard deviation of travel time.

Buffer measures

Buffer measures attempt to present how much "buffer" time is to be allowed in a trip to make sure that travelers arrive at a destination on time given the uncertainty of traffic conditions. This concept is related to a traveler's trip decision making process.

- Buffer time (*(23)*)

  Buffer time is 95th percentile travel time minus average travel time. This is the additional allotted trip time beyond the average to allow for on time arrival in 19 cases out of 20. That is, for a typical commuter the rate of failure (e.g. being late for work) is approximately once a month.

- Buffer index (*(5, 23, 34)*)

  Buffer index is the size of buffer as a percentage of the average travel time. It can be calculated by dividing buffer time by average travel time.

- Planning time (*(5, 34)*)

  Planning time is 95th percentile of travel time. This can be a planning travel time that a traveler expects to achieve on-time arrival. Planning time is the sum of buffer time and average travel time.

- Planning time index (*(5, 23, 34)*)

  This measure represents how much larger the buffer is than the ideal or free flow travel time, calculated as planning time divided by free flow travel time.

Tardy trip indicators

Tardy trip indicators represent the lack of reliability of a transportation system using the proportion of trips whose travel time is longer than an acceptable threshold.

- Florida reliability method (*(23, 28)*)

  The Florida Reliability Statistic is calculated as 100% minus the percent of trips with a travel time greater than the acceptable travel time, where the acceptable travel time is the expected (median) travel time plus an acceptable additional travel time (e.g. 5%, 10%, 15%, 20% of the expected travel time). This measure is still under development especially to determine how much percent should be used for the calculation of the acceptable additional travel time *(23, 30)*.

- On-time arrival (*(23)*)

  This measure is similar to Florida Reliability Statistic but it uses average travel time instead of median as the expected travel time.

- Misery index (*(23)*)

  This measure represents the worst day of week travel condition compared to the average. The calculation is (average of the travel time for the longest 20% of all trips – average travel time for all trips)/(average travel time for all trips).

Efforts to incorporate reliability to congestion measurement

Since 2001 FHWA's Mobility Monitoring Program has been monitoring traffic congestion levels in participating cities (30 cities as of 2004) *(9)*. The reported measures include planning time index and buffer index. The Urban Mobility Report published by Texas Transport Institute has tracked the congestion patterns of 85 cities since 1982 and the buffer index since 2002. US DOT's Intelligent Transportation Infrastructure program, established in TEA-21, selected six performance measures for transportation systems with three of them related to reliability: travel time percent variation, travel time buffer index, and travel time misery index *(21)*. Reliability is also one of the four research focus areas in Strategic Highway Research Program II, authorized in the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETY–LU) *(10)*. At state level, in California DOT, Florida DOT, and Minnesota DOT the framework to develop transportation system performance measures include the concept of reliability *(21)* . In state of Oregon the buffer index has been chosen as one of the statewide operations performance measures *(35)*. Washington State DOT uses archived freeway operations data to provide several congestion measures including the 95 percent reliable trip travel time. Generally, the mentioned public transportation agencies use ITS traffic surveillance infrastructures as their primary data source with analysis typically limited to freeways.

Reliability trends in metropolitan areas

Along with congestion increasing travel time reliability has been decreasing in major metropolitan areas (

Table 3). For example, Figure 3 shows that the increase in the 95th percentile travel time is higher than the increase of mean travel time on I-75 in central Atlanta. This may explain the reason why the congestion monitoring programs include reliability measures in addition to average travel time.

Table 3: Buffer index trend in major metropolitan areas (population>3million)

year	Atlanta	Detroit	Houston	LA	Philadelphia	Phoenix	W. DC
2000	13%(1.14)	16%(1.14)	19%(1.17)	17 %(1.39)	N/A	15%(1.15)	N/A
2001	15%(1.19)	15%(1.12	19%(1.11)	25 %(1.35)	20%(1.22)	14%(1.15)	N/A
2002	15%(1.24)	20%(1.11)	22%(1.22)	26 %(1.42)	18%(1.22)	14%(1.17)	17%(1.17)
2003	17%(1.24)	17%(1.12)	26%(1.29)	27 %(1.43)	19%(1.21)	16%(1.16)	21%(1.29)

Note: buffer index=(95th percentile time-mean travel time)/mean travel time and parenthesis includes travel time index=mean travel time/free flow time. Source *(9)*.

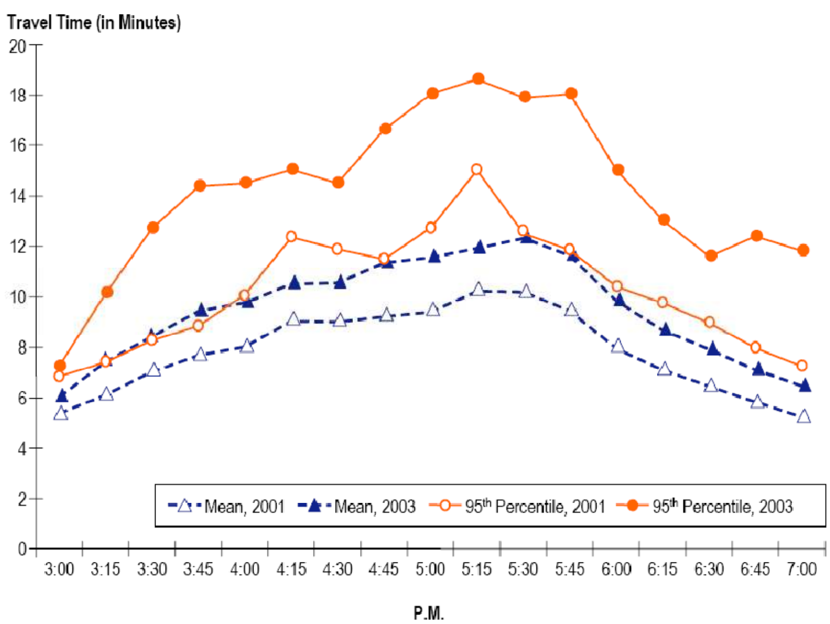


Figure 3: Central Atlanta I-75 4 mile segment mean and 95 percentile travel time on Thursdays in 2001 and 2003
Source *(5)*

Previous arterial (adaptive) traffic control system performance evaluation studies

The average travel time or change in speed on major corridors are commonly examined in existing evaluation studies of adaptive traffic control in the U.S. For testing the changes of minor street performance, intersection delays from minor approaches, and major turning approaches were investigated in the evaluation of SCATS in Oakland County, Michigan *(36)*, Gresham, Oregon *(37)*, Cobb County, Georgia *(38)*, and Park City, Utah *(39)*, and OPAC on Route 18 in New Jersey *(40)*. No study found that the tested system was absolutely better than the previous time-of-day system, but based on conclusions or results of these studies and others, the tested adaptive traffic control systems either generally improved the traffic conditions (SCATS Oakland County, Michigan *(36)*, SCATS Hennepin county, Minnesota *(41)*, SCATS Gresham, Oregon *(37)*, SCATS Park City, Utah *(39)*, OPAC New Jersey *(40)*, and ACS-Lite Ohio, Texas, Florida *(42)*) or showed mixed results (SCATS Cobb County, Georgia *(38)*, OPAC Vancouver, Washington *(43)*, SCOOT Anaheim, California *(44)*, and SCOOT Minneapolis, Minnesota *(45)*). Among the studies that showed mixed results, it should be noted that SCATS in Cobb County, Georgia was comparable to a recently optimized time-of-day system and that SCOOT Anaheim, California was comparable to the previous system without changing the detection system to that required by SCOOT. The study of SCOOT evaluation in Minneapolis, Minnesota reported a qualitative comment by city traffic operators that they perceived an improvement although it was not obvious quantitatively. Table 4 summarizes these studies, in which the conclusion was made based on overall results of discrete time periods and road segments.

Table 4: Previous arterial traffic control system performance evaluation studies

System/location	# intersections	MOEs	Results	Conclusion
SCATS *(36)* Oakland county, Michigan	9 intersections on Orchard Lake Road	Corridor travel time Stopped delay of major and minor street at 3 intersections (NB thru, WB thru)	Corridor travel time decreased. Major approach delay decreased, but minor approach delay increased. Average delay of all approaches decreased.	Improved
SCATS *(41)* Hennepin county Minnesota	68 intersections along southern beltway (I-494)	Travel time, speed, delay, number of stops of 22 corridors	60% of corridors showed improvement (10% significance level, after traffic demand change adjustment)	Improved
SCATS *(37)* Gresham, OR	11 intersections on Burnside Road	Travel time, delay, number of stops of 3 corridors Side street intersection delay at 3 intersections	Major corridor travel time decreased (5% significance level).	Improved
SCATS *(38)* Cobb County, GA	15 intersections on Atlanta Road, Paces Ferry Road, Cumberland Parkway	Travel time and delay of 2 corridors Travel time and delay of side street to side street traffic Intersection delay (6 intersections)	Major corridor travel time increased, but minor corridor and major-minor composite corridor travel time decreased (5% significance level).	Mixed
SCATS *(39)* Park City, Utah	12 intersections on SR 224, 248	Travel time, delay, number of stops of main corridor Intersection delay at 3 intersections	Most MOEs decreased (5% significance level).	Improved
OPAC *(43)* Vancouver Washington	12 intersections on Mill Plain Blvd	Corridor speed (EB, WB)	EB speed increased and WB speed (5% significance level).	N/A
OPAC *(40)* New Jersey	15 intersections on Route 18	Travel time, number of stops of 2 corridors Side street intersection delay at 2 intersections	During PM-peak, SB corridor travel time decreased, but side street delay increased (5% significance level).	Effective
SCOOT *(44)* Anaheim California	22 intersections	Travel time, intersection delay	SCOOT and baseline system were comparable.	Mixed but worth pursuing

Table 4: Continued

System/location	# intersections	MOEs	Results	Conclusion
SCOOT *(45)* Minneapolis, MN	56 intersections in Minneapolis CBD	Travel time of 6 corridors	In normal traffic condition, neither system was dominating. During special event, travel time decreased.	Analyses of test runs showed mixed results but city operators perceived an improvement.
ACS-Lite *(42)* OH TX FL CA	9 intersections on Hamilton Road Columbus, OH 8 intersections on Route 6 Houston. TX 8 intersections on Route 70 Tampa, FL 10 intersections Main St San Diego, CA	Delay, stop, fuel	All MOEs decreased except fuel consumption increase in San Diego.	N/A

Reliability measure selected for adaptive traffic control performance evaluation

In a recent Transportation Research Board publication seven sources of travel time variability are identified: traffic incidents, work zone, weather, fluctuations in demand, special event, traffic control device, and inadequate base capacity *(6)*. Also the FHWA identified seven sources of traffic congestion: bottleneck, traffic incidents, work zone, bad weather, poor signal timing, special event, fluctuations in normal traffic *(32)*. In both studies fluctuations in demand and traffic signalization are identified as sources of unreliability and congestion. Adaptive traffic control is an advanced control system designed to respond to real time traffic variability. Should this prove true it may also have the benefit of reducing unreliability caused by traffic demand fluctuation. Furthermore incidents, special event and adverse weather condition may be treated better by adaptive traffic control system.

Summary

In transportation engineering, travel time reliability generally reflects the consistency and the predictability in travel time. Given its importance to road users, transportation related agencies have developed and monitored reliability measures. The monitoring programs have found that as congestion increases, travel time reliability generally decreases. Although reliability has been recognized as an important performance measure, it has been primarily limited to freeway operation, rarely covering arterial traffic. Adaptive traffic control is an advanced traffic management system for urban signalized arterials with the ability to adjust control parameters in response to traffic conditions. Since the variability of traffic demand and signalization have been identified as sources of low travel time reliability it is recommended that travel time reliability should be included in the evaluation of an adaptive traffic control system.

CHAPTER 3. DATA

This chapter presents the study area, data collection time, data collection method, and data reduction algorithm. The algorithm is summarized in this chapter and its detailed discussion and application examples are found in the author's publication *(46)*, a copy of which is also found in Appendix A.

The *Highway Capacity Manual 2000* defines an arterial street as a type of urban street serving long through trips and yet providing access to commercial and residential land uses adjacent to it *(47)*. An arterial street tends to have a high traffic volume, high operating speed, and frequent connections with other arterials and collectors. These characteristics usually justify traffic control thus urban corridors typically contain multiple signalized intersections which govern the arterial performance.

Performance of an urban arterial is usually measured by average travel time or average travel speed, both of which are widely accepted congestion indices *(48)*. The *Highway Capacity Manual 2000* also defines arterial street level of service according to the average through travel speed of the arterial *(47)*. Since the travel speed is calculated from the travel time, travel time is a major concern of transportation researchers and engineers who want to measure quality of service on arterial streets.

Traditionally, travel time data have been collected using the test vehicle technique or floating car method. For example, a driver is instructed to overtake as many vehicles as he/she is overtaken by, resulting in the car "floating" in traffic stream *(49)*. One of three instrumentation levels are commonly utilized for this type of study: manual method, distance measuring instrument (DMI), and global positioning system (GPS) *(50)*. Since a passenger must be in the vehicle to record the cumulative time along the study route, the manual method is the most labor-intensive and susceptible to human errors. In contrast, DMI's utilize optical sensors connected to the vehicle transmission or one of the wheels and automatically record travel time, speed and distance *(51)*. While DMI technology can provide an accurate record of travel time *(52)* there are several drawbacks: the DMI unit is vehicle-dependent, frequently calibration is required, and the vehicle's tire pressure should be verified before every data collection effort *(51)*.

GPS technology was originally developed for tracking military ships and vehicles. GPS has the advantage of locating objects based on a satellite signal, which is available anywhere on earth. Given the ease of use the consumer market in civil, commercial, and research areas has seen significant growth *(50)*. Like DMI technology, GPS technology records data automatically, reducing labor costs and human errors. Data collection can be independent of an individual vehicle through the use of a portable system consisting of a GPS receiver and a palmtop (PDA) or a laptop connected to the receiver. Unlike DMI technology, which requires permanent equipment installation to a dedicated vehicle, drivers can utilize their personal vehicle for data collection, resulting in decreased bias due to driver unfamiliarity with the vehicle. Also, the collected data can be easily integrated with a geographic information system (GIS) environment.

This study uses the GPS test vehicle travel time data collected for a Georgia Tech study of the Cobb County initial SCATS installation *(38)*. Before the new control was introduced in early 2005, the intersections were operated under time-of-day semi-actuated coordinated control, referred to as ACTRA. As part of this study, various data collection routes were prepared and travel time data were collected under ACTRA and

SCATS signal operation. An automated GPS test vehicle data reduction algorithm was also developed.

Study area

The Cobb County SCATS pilot study area, Figure 4, is located in southeast portion of Cobb County, Georgia. The study area is comprised of fifteen intersections (numbered from 7 to 21 in Figure 5) on three arterials: Atlanta Road, Paces Ferry Road, and Cumberland Parkway. The majority of the systems lie on a two mile stretch of Paces Ferry Road, from the intersection of Atlanta Road and Paces Ferry Road on the west end to the intersection of Paces Ferry Road and Paces Mill Road on the east end. The west end of the study area is primarily a four-lane residential collector street (with a small strip mall on Atlanta Road) until just prior to the I-285 and Paces Ferry Road interchange, where the development character is that of office parks, shopping centers, and hotels. The east end of the study area (primarily a two-lane arterial), passes through an area with a mix of office parks, shopping, and residential uses. The speed limit in the study area is 35 mph except a 45mph speed limit for Atlanta Road.

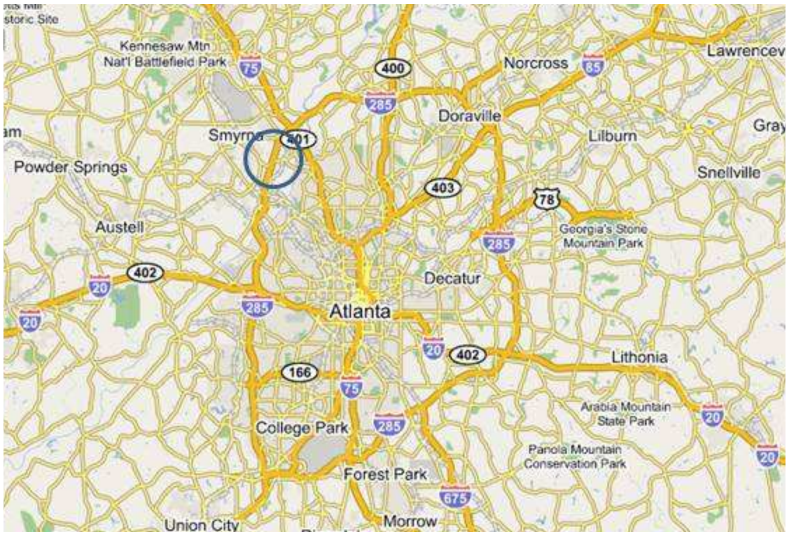


Figure 4: Cobb County SCATS pilot study area (inside the circle)
Map source: maps.google.com

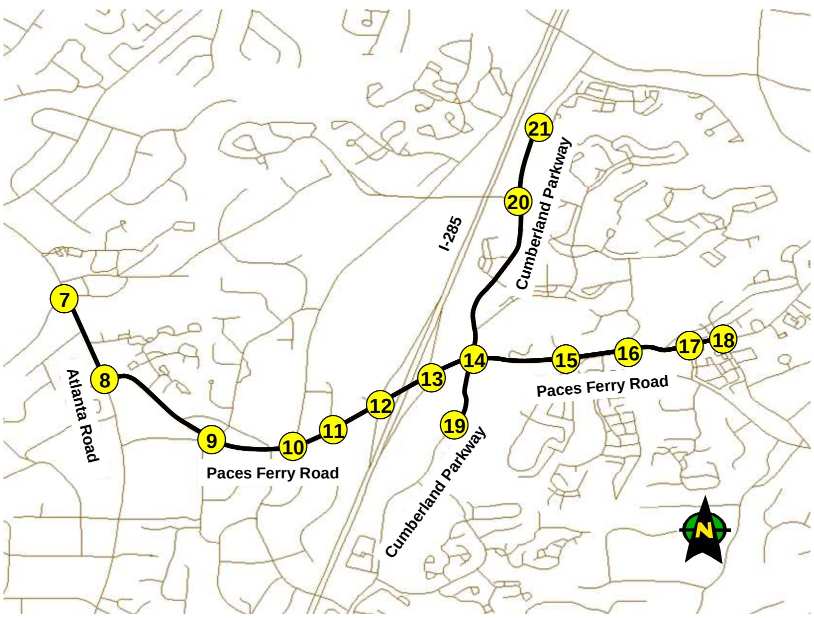


Figure 5: SCATS pilot study area intersections
Map source: Georgia Department of Transportation Highway Performance Monitoring System

Field data collection

There are several important steps that were completed prior to gathering GPS field data: configuring a test vehicle, selecting travel time routes, determining necessary sample size, and conducting a pilot study.

Test vehicle configuration

For travel time data collection, GPS instrumented test vehicles were adopted. The utilized GPS system consists of a laptop or PDA, GPS receiver, external antenna, and power cable. Satellite signals are received by the antenna, processed by the receiver, and stored in the laptop or PDA. The equipment utilized for this study included:

- A HAiCOM 303E Multi-Mode Foldable GPS Receivers, having a stated positional accuracy of 10m with 95% confidence interval.
- A HP iPAQ h2215 PDA for storing data.
- The JAMAR GPS2PDA PDA software program to record the GPS data stream.
- A HAiCOM GPS antenna, attached on the driver's side roof to aid in minimizing multi-path error, e.g., the interruption of satellite signals by objects like vegetation or buildings *(53)*.
- A vehicle driven by the data collection driver.

With this system, time, speed, latitude, longitude, horizontal dilution of precision (HDOP), and number of satellites are recorded at one-second intervals. In addition to the GPS equipment, a log sheet was maintained by each driver to record start time, end time, route ID, and any comments (i.e., incidents, potential collection errors, construction, etc.) for each run.

Travel time data collection routes: fixed and random routes

Typically, urban arterial street signal coordination systems are designed to facilitate through movement. Thus, a test vehicle conducting end-to-end travel time runs has a high likelihood of predominantly sampling vehicles in the through green band. For longer arterial sections where a level-of-service based on through vehicle movement is of interest, end-to-end travel time runs may provide reasonable data. However, when attempting to determine intersection approach performance, it is likely that end-to-end travel time runs will result in biased delay values. Vehicle origin-destination (O-D) paths that tend not to be in the green-band will be underrepresented. For example, end-to-end test vehicle travel time data may not reflect the delays incurred by traffic originating from an upstream intersection side-street that has not yet entered the green-band. Sampling only vehicles from the upstream through movement may result in significantly higher or lower estimates of the true approach delay *(52)*. End-to-end runs also provide no information on side-street approach delays. To overcome these deficiencies, two different route types were utilized in this research: fixed and random. For fixed routes, drivers were instructed to travel along the given routes based on a path through the study area (i.e. end-to-end travel time runs). For random routes, drivers were given a series of randomly selected O-D intersection pairs within the study corridor, with each travel time run beginning and ending on an O-D intersection side street.

Eight fixed routes were designed to capture the dominant movements through the corridor, with the major exception that the travel time routes do not directly reflect vehicle access to I-285, instead capturing both through and turn movements at Cumberland Parkway. The routes were selected to best represent the end-to-end travel patterns as O-D traffic count data is not available. The utilized eight fixed routes are shown in Figure 6 and their origin and destination intersections are presented in Table 5. For convenience these routes are labeled as A though H.

Table 5: Origin and destination intersection ID of fixed routes

Route	A	B	C	D	E	F	G	H
Origin	7	18	7	21	19	21	18	21
Destination	18	7	21	19	7	18	19	19

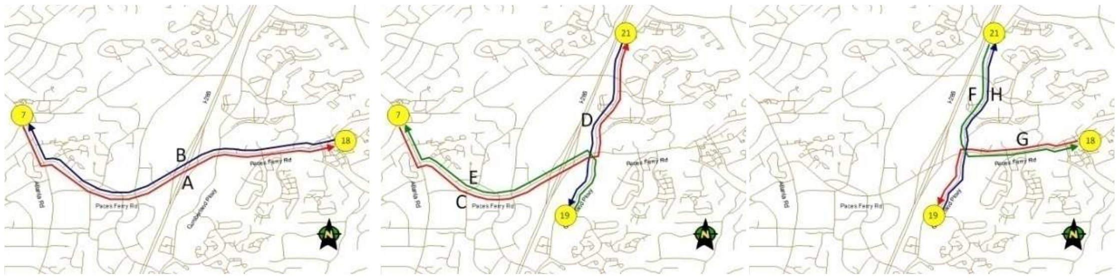


Figure 6: Fixed test vehicle routes
Map source: Georgia Department of Transportation Highway Performance Monitoring System

The random routes were devised to collect the delays of vehicles turning from the major street to a side street, delays of vehicles entering the major road from a side street, and travel time along the major street of vehicles originating from a side street. For this study, the random route travel runs concentrated on Paces Ferry Road and Atlanta Road and did not incorporate Cumberland Parkway. Figure 7 demonstrates a set of sample random routes. Random routes where selected such that the vehicles path during the data collection period consisted of a series of randomly selected intersection-to-intersection traverses along Paces Ferry Road. In developing the random routes the test vehicles start from a minor street, turning right or left onto major streets with an equal likelihood. The test vehicle travels a randomly selected number of intersections, turning left or right onto the minor road at the last intersection of their route. The vehicle then starts their next random traverse of the corridor from the current side street. For example, at the start of the data collection period a vehicle would begin on the side street of an intersection near the mid-point of the Paces Ferry Road corridor. The vehicle would turn onto Paces Ferry

Road heading eastbound or westbound with equal probability (i.e. 50-50 chance of going in either direction.) The vehicle would travel two to six intersections, again each distance having an equal probability. Upon reaching the destination intersection the vehicle would randomly turn left or right from Paces Ferry Road. The process would then continue from that side street. Figure 7 shows the first four legs of a randomized set of travel runs, with the insert graph showing a random path consisting of 30 intersection-to-intersection traverses.

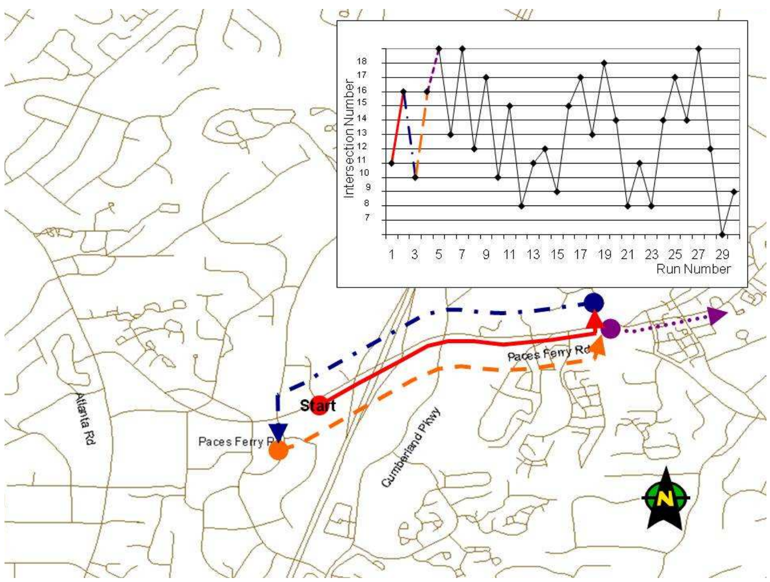


Figure 7: Random test vehicle routes

Travel time data collection period

Table 6 lists the time frame and number of data collection days for the ACTRA and SCATS data collection, for both fixed and random route data collection methods. Before SCATS timing implementation data collection was from November 9, 2004 to December 8, 2004, and after data collection was from April 12, 2005 to May 15, 2005. No data was collected during the week of, or the weekends adjacent to, the Thanksgiving holiday. Travel time data was collected from 7 AM to 1 PM and from 5 PM to 7 PM on weekdays, from 12 PM to 4 PM on Saturdays, and from 10 AM to 2 PM on Sundays. Thus, data was collected during the weekday morning peak, weekday off-peak, weekday evening peak, and weekends. In the later analyses, the data were aggregated into six groups: four weekday periods (7:00 to 9:00, 9:00 to 11:00, 11:00 to 13:00, 17:00 to 19:00) and two weekend periods (Sat 12:00 to16:00, Sun 10:00 to 14:00).

Table 6: Travel time data collection period

	Travel Time Study			
	Fixed Route		Random Route	
	Before	SCATS	Before	SCATS
From	11/9/2004	4/12/2005	11/30/2004	5/3/2005
To	12/8/2004	5/1/2005	12/5/2004	5/15/2005
Number of Weekdays	6	8	3	6
Number of Weekend days	4	6	2	4

Sample Size

Table 7 and Table 8 list the number of runs conducted during each time period for the fixed and random route data collection methods, respectively. The total number of travel runs conducted was based on a compromise between the desired statistical significance and the available resources (both financial and available time frame) to conduct the travel time data collection effort. Given the relatively high number of time periods under consideration (weekday morning peak, weekday off-peak, weekday afternoon peak, weekday evening peak, and weekends) and the need for a high sensitivity in the ACTRA/SCATS comparison, a large number of travel runs were conducted. For the fixed route comparison a total of 736 travel runs were conducted in ACTRA data collection and 927 travel runs in SCATS data collection (a travel run is defined as each end-to-end vehicle trip). For the random route data collection 479 ACTRA travel runs and 758 SCATS travel runs were conducted (a random route travel run is defined as an intersection-to-intersection trip). The number of runs conducted for SCATS study was higher than that for the before study, due to experience (and subsequent efficiencies) gained during the ACTRA data collection and the longer available data collection window for the after study. Table 7 and Table 8 list the travel runs completed by time period for the fixed and random route data collection efforts.

Table 7: Fixed route travel time data collection summary

<table>
<tr><td rowspan="2">Time Period</td><td colspan="3">Before</td><td colspan="3">After</td></tr>
<tr><td colspan="2">Weekday</td><td>Weekend</td><td colspan="2">Weekday</td><td>Weekend</td></tr>
<tr><td>7:00-8:00</td><td>52</td><td rowspan="2">115</td><td rowspan="2">N/A</td><td>69</td><td rowspan="2">128</td><td rowspan="2">N/A</td></tr>
<tr><td>8:00-9:00</td><td>63</td><td>59</td></tr>
<tr><td>9:00-10:00</td><td>43</td><td rowspan="2">93</td><td>29</td><td>75</td><td rowspan="2">155</td><td>40</td></tr>
<tr><td>10:00-11:00</td><td>50</td><td>39</td><td>80</td><td>34</td></tr>
<tr><td>11:00-12:00</td><td>54</td><td rowspan="2">102</td><td>52</td><td>96</td><td rowspan="2">165</td><td>68</td></tr>
<tr><td>12:00-13:00</td><td>48</td><td>67</td><td>69</td><td>75</td></tr>
<tr><td>13:00-14:00</td><td>4</td><td rowspan="2">4</td><td>31</td><td>4</td><td rowspan="2">4</td><td>43</td></tr>
<tr><td>14:00-15:00</td><td>0</td><td>42</td><td>0</td><td>47</td></tr>
<tr><td>15:00-16:00</td><td>0</td><td rowspan="2">19</td><td rowspan="4">N/A</td><td>0</td><td rowspan="2">1</td><td>8</td></tr>
<tr><td>16:00-17:00</td><td>19</td><td>1</td><td rowspan="3">N/A</td></tr>
<tr><td>17:00-18:00</td><td>80</td><td rowspan="2">143</td><td>74</td><td rowspan="2">159</td></tr>
<tr><td>18:00-19:00</td><td>63</td><td>85</td></tr>
<tr><td rowspan="2">Total</td><td colspan="2">476</td><td>260</td><td colspan="2">612</td><td>315</td></tr>
<tr><td colspan="3">736</td><td colspan="3">927</td></tr>
</table>

Table 8: Random route travel time data collection summary

<table>
<tr><td rowspan="2">Time Period</td><td colspan="3">Before</td><td colspan="3">After</td></tr>
<tr><td colspan="2">Weekday</td><td>Weekend</td><td colspan="2">Weekday</td><td>Weekend</td></tr>
<tr><td>7:00-8:00</td><td>51</td><td rowspan="2">95</td><td rowspan="2">N/A</td><td>68</td><td rowspan="2">125</td><td rowspan="2">N/A</td></tr>
<tr><td>8:00-9:00</td><td>44</td><td>57</td></tr>
<tr><td>9:00-10:00</td><td>42</td><td rowspan="2">70</td><td>2</td><td>63</td><td rowspan="2">147</td><td>6</td></tr>
<tr><td>10:00-11:00</td><td>28</td><td>25</td><td>84</td><td>3</td></tr>
<tr><td>11:00-12:00</td><td>28</td><td rowspan="2">62</td><td>33</td><td>84</td><td rowspan="2">164</td><td>68</td></tr>
<tr><td>12:00-13:00</td><td>34</td><td>47</td><td>80</td><td>46</td></tr>
<tr><td>13:00-14:00</td><td rowspan="4" colspan="2">N/A</td><td>25</td><td>4</td><td rowspan="2">4</td><td>29</td></tr>
<tr><td>14:00-15:00</td><td>29</td><td>0</td><td>9</td></tr>
<tr><td>15:00-16:00</td><td rowspan="4">N/A</td><td>0</td><td rowspan="2">2</td><td rowspan="4">N/A</td></tr>
<tr><td>16:00-17:00</td><td>2</td></tr>
<tr><td>17:00-18:00</td><td>49</td><td rowspan="2">91</td><td>73</td><td rowspan="2">155</td></tr>
<tr><td>18:00-19:00</td><td>42</td><td>82</td></tr>
<tr><td rowspan="2">Total</td><td colspan="2">318</td><td>161</td><td colspan="2">597</td><td>161</td></tr>
<tr><td colspan="3">479</td><td colspan="3">758</td></tr>
</table>

Pilot Study

Prior to ACTRA data collection, a travel time run data collection pilot study was conducted to avoid potential confusion, errors, and the unnecessary loss of data during the full data collection effort. The pilot study provided a very useful opportunity for debugging and revising the data collection protocols prior to the full scale data collection effort. During the pilot study, all devised procedures were tested and the data collection team was familiarized with the proposed process. Tasks accomplished as part of the pilot study included:

- Confirm defined route starting/ending locations to provide safe maneuvering for test vehicle drivers.
- Confirm adaptability of the adopted GPS equipment in different test vehicles along the selected routes. That is, any significant scattering or occlusion, loss of satellites, etc. that may affect the GPS reliability are checked.

- Ensure that given driver instructions are clear and understandable.
- Estimate route travel times so that the data collection plan can be fine-tuned.
- Ensure that drivers are familiarized with equipment (GPS hardware and software), and driver log, and traveled routes.

Through the pilot study the data collection plan was debugged and revised before the full scale data collection. For example, the GPS equipment adopted in the study contained an interface that required the driver or a passenger assistant to press a button on the PDA when the test vehicle passed through the subject intersection. After the pilot study, most of the assistants responsible for pressing the button reported feeling motion sickness. Thus, it was found that developing additional post-data collection processing algorithms that relieved the data collection personnel of any interaction with the equipment during a travel run.

GPS data processing

The GPS data processing procedure generates link-based travel times. The raw data files contain a row of data for each GPS point (i.e., each second of data) containing time stamp, latitude, longitude, speed, HDOP (Horizontal Dilution of Precision), and number of satellites. Each travel run is processed such that a run ID is added to each GPS data point and a unique ID is assigned to every intersection and turn-around point. The run ID is coded to reflect the date, route ID, and cumulative run number. These IDs allow for comparing GPS data files with driver log sheets and maintaining project organization, particularly when large numbers of runs are conducted over multiple days.

Data quality control

Prior to final travel time analysis a thorough data error checking procedure was implemented. This procedure addressed both driver and equipment errors. Driver errors are primarily identified through notations made on the driver log sheet, typically including: 1) starting data collection before initialization of GPS system, 2) missing a turn on the designated travel route, and 3) failing to stop GPS data recording between runs. The data corresponding to travel runs with the first two types of errors were removed from further consideration, and the third error was addressed by splitting the combined file into two files, each containing an individual travel time run. In addition to driver errors, travel runs in which a driver noted an incident on the corridor were separated from the primary analysis files. It was hoped that a significant number of travel runs affected by an incident might be obtained to allow for further analysis; however a significant example was unfortunately not obtained.

After addressing driver-related errors, the remaining data was scanned for potential GPS-related errors. Ogle et al. provides a detailed discussion of the sources of GPS error *(54)*. Based on these error sources and the conducted pilot study, the following criteria were developed to identify potentially erroneous data points: distance from the previous point, speed change from the previous point, HDOP, and number of satellites. The distance between consecutive points, speed change, and HDOP criteria each require user judgment and may change based on study conditions. Guidance for setting these criteria are presented in the next section, Sensitivity Analysis.

After data points were identified as potential errors, the following actions (*(47)*) were taken:

- If an erroneous point is isolated, its data fields are replaced with interpolated values from points one second before and after the point.
- If a large number of error points exist in a run, the run is visually reviewed using GIS environment. If the visual inspection cannot confirm the accuracy or reasonable interpolation is unavailable to correct the points the run is eliminated in later analysis.
- If the number of error points is low, the run is kept, and an error flag is added to the potential error points' fields. The data reduction algorithm developed as part of this study includes an error filtering routine to ensure that points flagged as potential errors are not passed to later analysis.

Only travel runs with a high number of error points are eliminated in an effort to balance loss of data and potential errors that may be introduced into the analysis. For this study a value of 10% of the total number of GPS points in a run was considered significant and warranted elimination of an entire run. Where fewer than 10% of the GPS points were identified as potential errors the filtering step in the developed travel time algorithm was used to ensure analysis accuracy. These criteria were designed to provide a conservative evaluation of the data, ensuring the accuracy of the final travel time analysis.

Travel Run Intersection Passing Time Identification (TRIPTI) algorithm

The intersection-to-intersection travel time on an arterial street is a function of the driver's desired speed on the link and any delay they may experience. The intersection-to-intersection travel time delay includes delay experienced while traversing the link and delay at the downstream intersection. To ensure that the downstream intersection delay is assigned to the proper arterial segment, travel time is calculated from immediately past the upstream intersection to immediately past the downstream intersection. The Travel Run Intersection Passing Time Identification (TRIPTI) algorithm, developed as part of this research effort, is utilized to identify the time at which a test vehicle completes its pass through an intersection and determine the travel time between intersections. The final product of the TRIPTI algorithm is the time stamp at which the vehicle passes the intersection and the intersection IDs recorded for each intersection traversed in the travel run. Based on the output from the TRIPTI algorithm, travel time, average delay, average speed, standard deviation of travel time, etc. for *any* two intersections included in the travel runs, not just consecutive or beginning and ending intersections, may be determined and stored in a database. An example of the developed database is found in Figure 8, in which i and j are origin and destination intersection ID respectively. This database allows for extensive flexibility in interpreting travel time results by considering different corridor segment lengths, from between consecutive intersections, to corridor sections incorporating several intersections, to the entire corridor. A complete discussion and an application example of the TRIPTI algorithm are found in Appendix A.

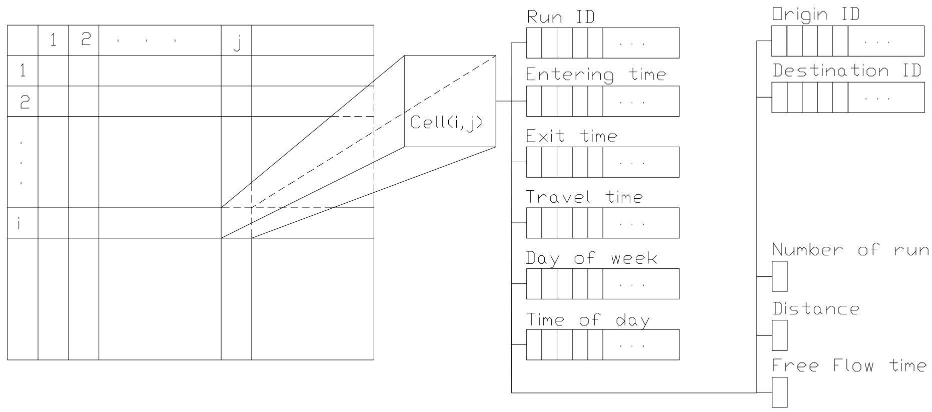


Figure 8: Example of developed travel time database

Sensitivity study

As mentioned earlier, after addressing driver-related errors, the remaining data must be scanned for potential GPS-related errors. The following criteria were developed to identify potentially erroneous data points: distance from the previous point, speed change from the previous point, HDOP, and number of satellites. The distance between consecutive points, speed change, and HDOP criteria require user judgment and may change based on study conditions. This section presents the rationale for the selected criteria of which the detailed discussion is found in *(55)*.

Distance between consecutive points

The maximum reference value for this criterion is obtained based on the maximum speed reported from the test vehicle run drivers. For example, the drivers of the travel time study reported that a maximum speed, including all periods of data collection effort, of approximately 50 mph. To allow for some error buffer in their perception and reasonable GPS speed approximations, 55 mph was selected as a realistic maximum speed. Thus, a critical value of 80.67 feet (the distance traveled at 55 mph in one second) was selected as the maximum allowable distance between consecutive GPS points. Where the distance between two consecutive GPS points were over 80.67 feet, an error flag is put to the second GPS point. The sensitivity analysis results exhibit that more than 99.7% of the total data points collected fell below this value.

Speed Change Criteria

Maximum acceleration and deceleration rates are defined for the speed change error criterion. The values represent the possible speed change in a second in this study. Where acceleration and deceleration rates are above the set values, the latter GPS point should be flagged as a potential error point. The chosen values in this study were 10.76 mph/s and -11.2 mph/s for acceleration and deceleration, respectively, which are based on the ITE *Traffic Engineering Handbook (56)* and AASHTO's *A Policy on Geometric Design of Highways and Streets (57).* At the beginning, a lower acceleration rate was adopted, but an analysis of the data showed that a significant number of points were labeled as error points, which actually appear reasonable considering the adjacent GPS points and the entire trip. Thus, it was determined that a higher cutoff value than the maximum acceleration rate found in the ITE guide was utilized. For the critical value of the deceleration rate, this study used -11.2 mph/s presented by AASHTO as the comfortable deceleration rate for most drivers. The sensitivity analysis for this criteria shows that less than 0.1% of the data violated the selected acceleration and deceleration criterion, respectively. As part of these criteria, the GPS equipment failure to report a speed value was also checked. The GPS equipment reported this by a value of -1 as the speed of a GPS point.

HDOP Criteria

HDOP tells the quality of the geographic configuration, i.e. relative locations of satellites at the moment a GPS point is recorded *(53)*. Recommended HDOP values are below four, and GPS points of values above eight should not be used *(58)*. The HDOP cutoff criterion adopted in any study requires a balance between desired accuracy and loss of potentially sound data. In this study, the maximum value selected for HDOP was four. The sensitivity analysis shows that the HDOP value of 93% of points was less than two and that of 98% was less than four. While a higher HDOP criterion (e.g., eight) may be utilized, as those points with HDOP values between four and eight that appeared questionable were likely also identified by the other criteria, the more conservative value of four was finally selected.

Number of Satellites Criteria

To determine positional information (x, y, and z coordinates) and clock bias of a GPS point, the technology must solve the four simultaneous equations *(48)*. To do this, the number of satellite must be four or more. Thus, if the number of satellite of any GPS point is less than four, the point should be considered as an error point.

Summary

In early 2005 the Cobb County DOT implemented the Sydney Coordinated Adaptive Traffic System (SCATS) on fifteen intersections along Paces Ferry Road, Cumberland Parkway, and Atlanta Road in an attempt to improve traffic flow, reduce congestion, enhance signal control responsiveness to incidents, and reduce signal re-timing costs.

This chapter described the evaluation study scope in time and space, data collection equipment, data collection procedures, and the developed data reduction algorithm.

The study area is located in southeast portion of Cobb County, Georgia. The travel time data were collected from November 9, 2004 to December 8, 2004 for ACTRA and from April 12, 2005 to May 15, 2005 for SCATS, using GPS-equipped test vehicles. The GPS technology can provide several benefits: reducing human errors, providing a short sampling rate, being independent of vehicles, and integrating with GIS environment.

The field data collection procedure includes the GPS equipment (PDA or laptop, GPS receiver, external antenna, and power cable), driver instruction, data collection routes, and a pilot study. Along with end-to-end type routes (fixed routes), random routes were devised. Typical urban arterial street signal coordination systems are designed to facilitate through movement. Thus, a test vehicle conducting end-to-end travel time runs has a high likelihood of predominantly sampling vehicles in the through green band. For random routes, drivers were given a series of randomly selected O-D intersection pairs within the study corridor, with each travel time run beginning and ending on an O-D intersection side street.

Initial data processing and error checking procedures were found to be essential. The initial processing gives IDs to the data sets that make the potentially very large data sets generated from GPS equipment manageable. The error checking procedure was to remove and identify error points that resulted from either drivers or the adopted GPS equipment. Potential point identification guides were presented for the distance between two consecutive data points, GPS point speed change, HDOP, and the number of satellites.

Once the data has been through initial and error checking procedures, the final data processing comprises two steps: the TRIPTI algorithm and database development. The TRIPTI algorithm automatically identifies the time a vehicle passes through an intersection on a travel time run. The database initially stores the intersection passing times for all intersection-to-intersection vehicle runs with the time stamps. After that, travel times between any two intersections that test vehicles passed can be calculated and stored as an array. The database can then be used for an easy calculation and analysis of relevant statistics required over differing study area sections and time periods. The major benefit from the algorithm and database is that statistics for any intersection origin-destination pair on travel time runs, not just consecutive intersections, may be determined. This provides great flexibility in analyzing travel time results, an analysis of different corridor segment lengths, from consecutive intersections to the entire corridor, for multiple time periods. Despite the advantages of the algorithm, it still needs to improve in two aspects: the overall procedure still requires considerable user interaction and is limited to travel times based only upon the time when a vehicle passes through an intersection. A complete discussion and an application example of the TRIPTI algorithm may be found in the author's publication *(46)* or in Appendix A.

The travel time data stored in the database are utilized for the analyses within this research effort. The fixed route data are used for the distribution analysis in Chapter 4, the reliability measure analysis in Chapter 5, and the system- wide performance development in Chapter 7. The random route data are used for the side street traffic performance analysis in Chapter 6 and also in Chapter 7.

CHAPTER 4. TRAVEL TIME DISTRIBUTION

Congestion causes urban street system operations to deteriorate in two ways: travel times increase and reliability decreases. Since most definitions of reliability attempt to capture some aspect of travel time variability it is clear that an assessment of urban street congestion that includes reliability is dependent on the characteristics of the underlying travel time distribution.

Along with geometric variables, one of the key performance factors in an urban street environment is traffic signal control, affecting travel time variability as well as average travel time. Although the goal of a typical traffic control system is to minimize an aggregate measure such as an average delay or the number of stops, individual vehicle travel times can vary significantly, particularly at higher traffic demands.

Given the interactions among congestion, travel time reliability, and traffic signal control, the goal of this chapter is to investigate the arterial travel time distribution under the compared control systems, ACTRA and SCATS. The collected travel time data are aggregated into the group of route, time period, and control type combinations and based on the group, travel time distribution or distribution-based statistics are compared and examined. For example, the field travel times are compared with known theoretical distributions, statistics describing the shape of the distributions, such as standard deviation, skewness, and kurtosis are examined related to congestion levels, and the inter-relationship among the shape statistics is presented. Based on the statistics, groups showing the extreme values are further investigated using histograms. Along with the histogram, a kernel density estimator is utilized for better visual comparison.

The literature on the arterial travel time distribution is reviewed in the next section followed by a description of the field data. The travel time distribution of the field data is then analyzed, followed by the chapter summary.

Review of arterial travel time distribution

Most previous studies on arterial travel time distributions found that travel time distributions tends to be skewed to the travel time higher values. In 1950s, one of the earliest studies on arterial travel time distributions, based on data collected on an arterial road in London, found that the arterial travel time distribution is often skewed with a long tail of slow trips *(59)*. Similar results were found in later studies. A study based on work trip data collected in Warren, Michigan and Fresno, California showed that the variation of trip time increases with the decreasing journey speed and that the trip time distribution is normal except the right tail *(60)*. Another study in Chicago, Illinois found that the travel time data are skewed to the right and that the gamma distribution fit the data well *(33)*. It also measured the reliability of an arterial using standard deviation of the data. Trip time data collected in Melbourne, Australia showed that the variability measured by the coefficient of variation of travel time increases as the congestion level increases and that the travel time distribution is skewed to the right. The log-normal distribution was applied to the data *(61)*. Commuting trip time data collected in Cambridge and Arlington, Massachusetts also showed that the log-normal distribution fit the data better than the normal distribution *(62)*. A study based on arterial travel time data in Irvine, California found that the log-normal or the gamma distribution is better than the normal distribution for characterizing the travel time on a signalized arterial *(63)*.

In contrast to the results above, other researchers have found that the normal distribution fit travel time data well, especially in peak conditions. For example, based on license plate data collected in San Francisco during peak periods, it was found that the travel time distribution for peak conditions is nearly normal *(64)*. In another example, morning and evening travel time data were recorded between London and Bray in England. The travel time was found to be normally distributed and the coefficient of variation of travel time was higher for the lower speed trips *(65)*.

Data

For the investigation of the travel time distribution under the compared systems, a well defined route should exist for an efficient comparison. As the random routes are roadway segments of different geometric characteristics and lengths, it would be difficult to define a consistent distribution. Thus the fixed route data only are used for the following analysis.

Data categorization

An attempt was made to categorize the collected data such that any effect of the control type on the travel time distribution could be identified. Presumably, travel time on urban streets largely depends on time periods (this assumes the traffic demand is largely dependent of travel time) and travel paths. The fixed route data are grouped by six time periods (four two-hour weekday periods and two four-hour weekend periods) and eight routes (A to H), resulting in forty-eight groupings under each control type. The sample size of the groups ranges from 8 to 31 travel time runs (Table 9).

Table 9: Sample size of time period-route-control group of fixed route data (unit: run)

Time period	Route								Grand total
	A	B	C	D	E	F	G	H	
ACTRA total	95	91	75	76	78	90	90	91	686
7:00~9:00	15	10	14	16	14	15	13	14	111
9:00~11:00	10	10	8	9	8	12	13	11	81
11:00~13:00	9	10	10	8	12	12	12	14	87
17:00~19:00	21	20	14	14	16	21	21	21	148
Saturday	18	18	14	14	13	14	15	15	121
Sunday	22	23	15	15	15	16	16	16	138
SCATS total	145	140	95	92	93	112	107	113	897
7:00~9:00	22	17	13	12	14	17	18	20	133
9:00~11:00	22	24	18	19	18	19	15	15	150
11:00~13:00	30	31	16	13	16	14	15	15	150
17:00~19:00	23	22	17	15	14	21	21	22	155
Saturday	25	23	15	17	15	24	23	25	167
Sunday	23	23	16	16	16	17	15	16	142
Grand total	240	231	170	168	171	202	197	204	1583

Comparison with theoretical distribution

The normal, log-normal, and gamma distribution were fit to the travel time distribution of the period-route-control groups using the maximum likelihood (see details in *(66)* or Appendix B). Then, the distribution of the field data were compared with the best fitting theoretical distributions using the Kolmogorov-Smirnov test (K-S test, see details in *(67)* or Appendix C). The null hypothesis is that the compared field distribution and the theoretical distribution are the same. With a 5 % significance level, no group showed a significant difference from any theoretical distribution. With a 10 % significance level, two ACTRA groups showed a significant difference from the normal distribution. With a 20 % significance level, three ACTRA groups and one SCATS group showed a significant difference from the normal distribution; three ACTRA groups and one

SCATS group showed a significant difference from the log-normal distribution; and three ACTRA groups showed a significant difference from the gamma distribution. In the test with the 20 % significance level, it is noticeable that two ACTRA groups showed a significant difference from all the three distributions and also that most of the significant cases belong to ACTRA groups. Based on the results, no strong evidence was found to reject the null hypothesis. However, this should not be taken to imply that the field travel time distribution in the study area can be well explained by all three theoretical distributions. The failure to reject the null hypothesis may be a result of the sample size not being large enough to make the test sufficiently sensitive to the differences. Therefore, the next section examines the shape of travel time distributions for further insights. The number of groups by the p-value of the K-S test is presented in Figure 9.

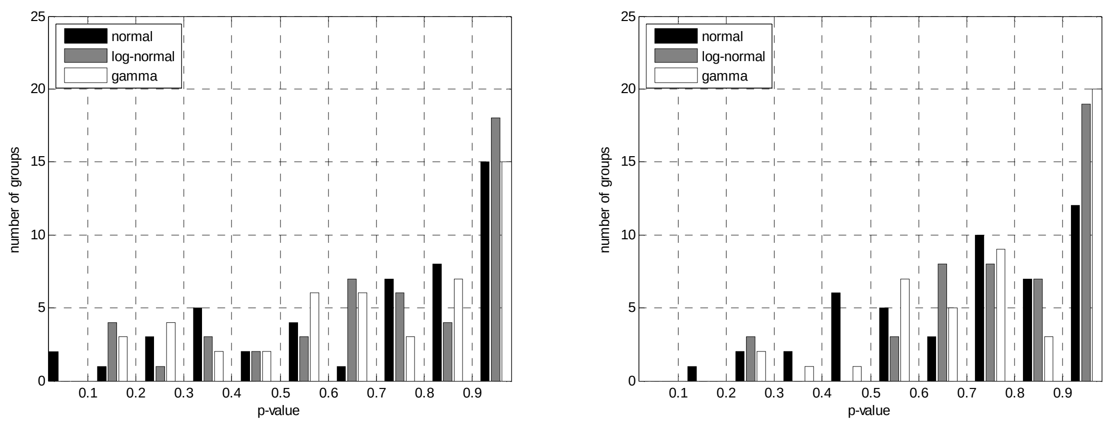


Figure 9: K-S test results: comparison of field travel time distribution and theoretical distribution for ACTRA data (left) and SCATS data (right)

Shape of travel time distribution

Adopted statistics describing shape of distribution

Standard deviation, skewness, and kurtosis (collectively referred to as shape statistics hereafter) describe the shape of a distribution in different aspects. Standard deviation measures the dispersion of a distribution. A higher standard deviation value means that the travel time is more variable. Skewness describes the degree of symmetry about the mean. It is zero for a symmetric distribution, such as the normal and the uniform distribution, positive for a distribution with an asymmetric tail toward larger values, and negative for a distribution with an asymmetric tail toward smaller values. Kurtosis describes the relative peakedness of a distribution with the normal distribution as its reference. That is, when higher proportion of data is closer to mean, the kurtosis value becomes higher. The kurtosis for the normal distribution is three (in some statistics literature three is deducted from the below definition, and it is zero) and a higher value means that the distribution is more peaked than the normal distribution. If an extremely high valued outlier exists in a distribution, standard deviation increases, skewness positively increases, and kurtosis also increases. The sample estimates for the three statistics are calculated by the following equations *(68)*:

Standard deviation (s) $\quad s = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$

Skewness (β_3) $\quad \beta_3 = \frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}\frac{(x_i-\bar{x})^3}{s^3}; n > 2$

Kurtosis (β_4) $\quad \beta_4 = \frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum_{i=1}^{n}\frac{(x_i-\bar{x})^4}{s^4}; n > 3,$

where, $x_i = ith\ observation$,

$\bar{x} = sample\ mean,$

$n = number\ of\ observation.$

Distribution of shape statistics

The three shape statistics were evaluated for the groups and the distributions of them were summarized for each control type in Figure 10. The distribution of standard deviation under the two control systems shows that the number of groups with dispersion (i.e standard deviation) greater than 1 minute decreased under SCATS. For the skewness SCATS decreased the number of groups that are left-skewed and extremely right-skewed, but increased the number of groups that are mildly right-skewed (0.5 < skewness < 1.5). For the kurtosis, the number of groups with its distribution flatter than the normal distribution (kurtosis < 2.5) decreased and that with relatively peak distributions (kurtosis > 3.5) increased under SCATS, but extremely peak distributions (kurtosis > 7.5) were observed only in ACTRA groups. Summarizing these results, the distributions under SCATS are less dispersed; more skewed but less extremely skewed; and more peak but less extremely peak (more groups closer to the peakedness of the normal distribution). The comparison of the statistics at individual route-period groups is shown in Figure 11, which illustrates that SCATS decreased the number of groups with the extreme values of the statistics.

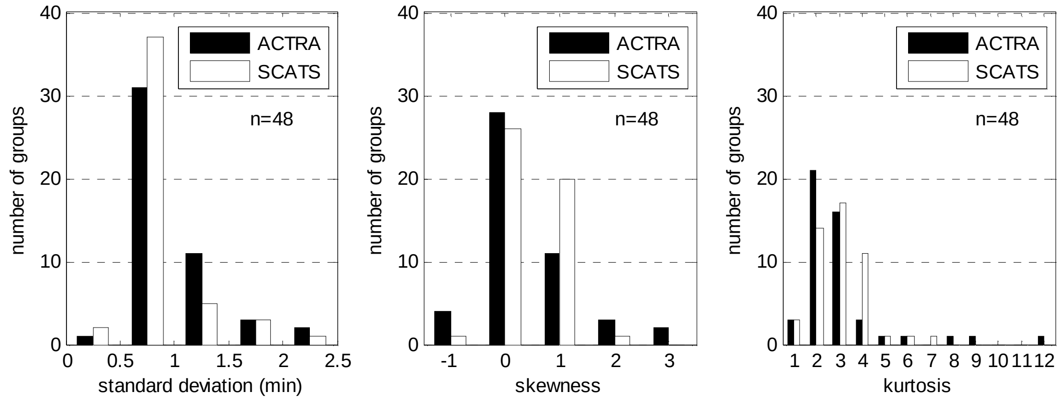


Figure 10: Distribution of standard deviation, skewness, and kurtosis under ACTRA and SCATS

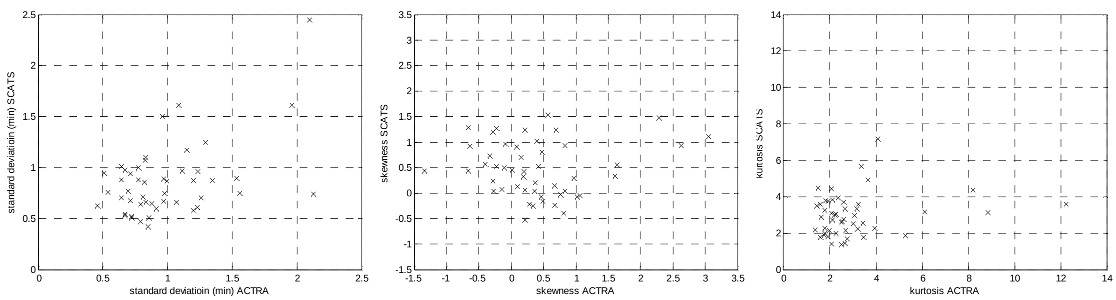


Figure 11: Comparison of the value of standard deviation, skewness, and kurtosis of individual route-period group

Shape statistics versus service quality

The Highway Capacity Manual 2000 defines the level of service (LOS) of an arterial based on the average travel speed *(47)*. To see the effect of the service quality on the shape of the travel time distribution, the three shape statistics were plotted against the average speed based on the group data (Figure 12 (left)). In place of standard deviation, coefficient of variation was used to normalize the effect of geometric conditions. The vertical lines indicate the LOS boundaries. The coefficient of variation of travel time appears to be proportional to the level of congestion. This trend is clearest at the lower LOS levels. However, in the likely uncongested conditions (i.e. LOS B and LOS C) the trend in the coefficient of variation is not as clear. Skewness and Kurtosis values do not show a clear increasing or a decreasing trend over the change of the service quality. It is noted that highest values of skewness and kurtosis are observed in ACTRA groups when the traffic is likely not congested (LOS “B” and “C”). Figure 12 (right) exhibits the boxplots of the statistics on LOS categories.

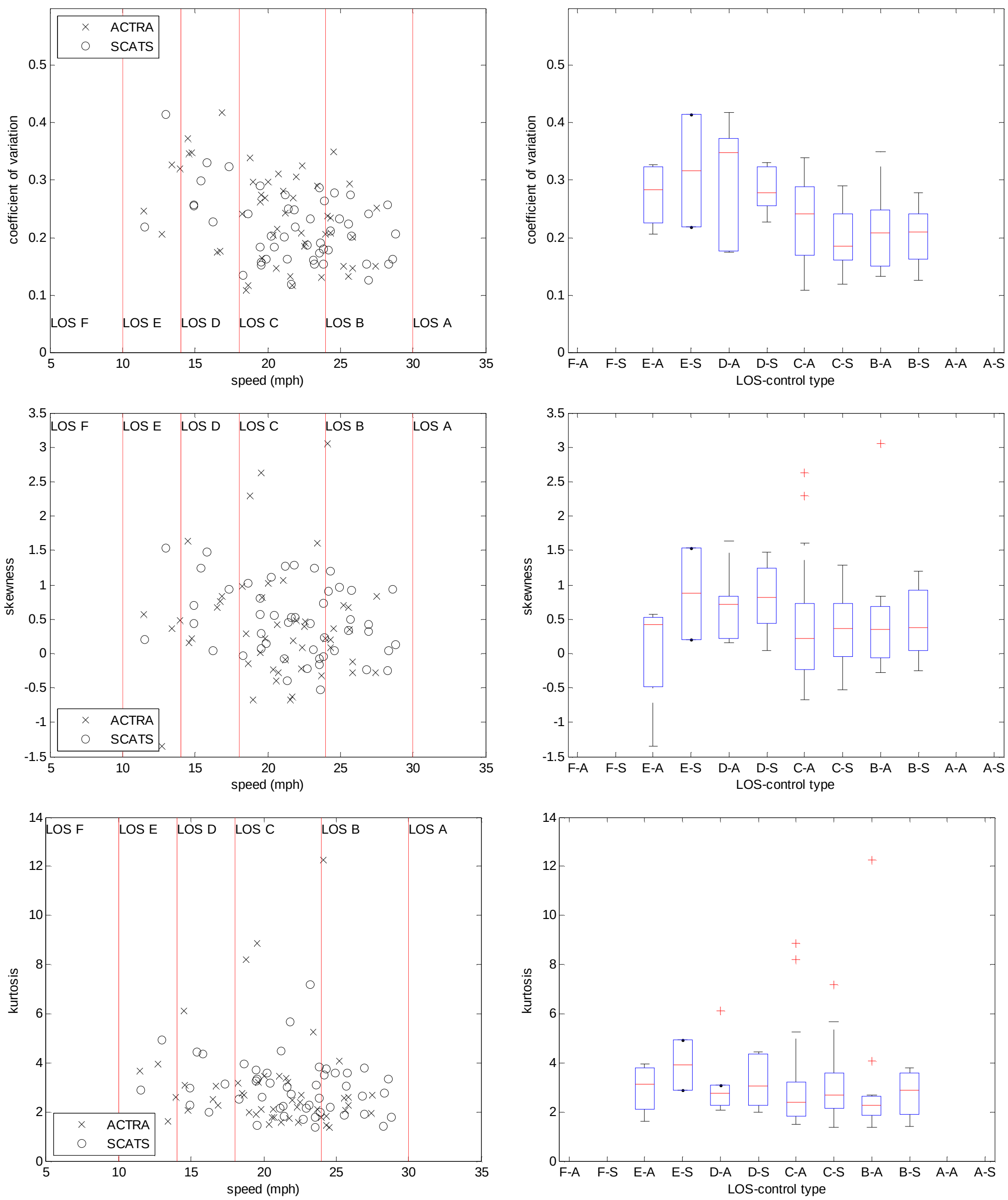


Figure 12: Shape parameters versus average speed (left) and level of service (right)

Relationship among shape statistics

The relationship among the shape statistics was examined next. Again, coefficient of variation was used in place of standard deviation as it is a dimensionless measure, as are kurtosis and skewness. As seen in Figure 13 neither skewness nor kurtosis shows a clear trend with coefficient of variation. However, the plot of skewness versus kurtosis shows a clear “<” shaped pattern, meaning that the value of peakedness is proportional to the absolute value of skewness in the travel time distribution. This is because a highly skewed distribution generally includes outliers that also increase the kurtosis value. Apart from a major portion of groups, four ACTRA groups are located with extremely positive (> 2) or negative (< -1) skewness. For those groups, a more detailed examination follows in the next section.

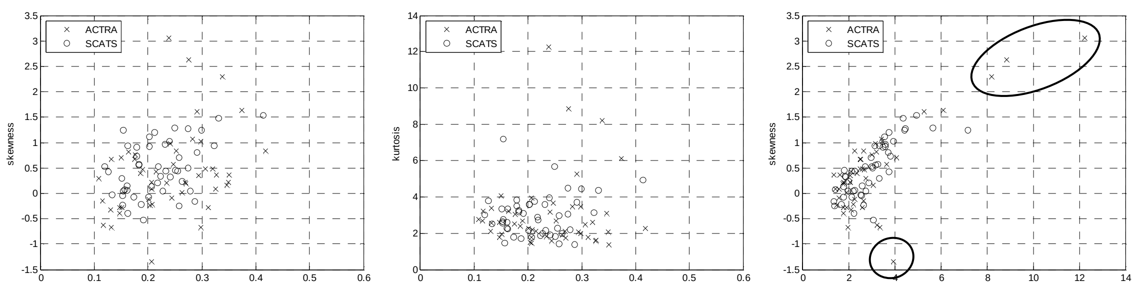


Figure 13: Relationship among statistics describing shape of distribution

Travel time distribution of groups with extreme skewness values

The four ACTRA groups (circled in Figure 13) may include extreme observations that make the skewness values extremely high or low. The travel time distribution of these groups was compared with that of the same route-period groups of SCATS. For this comparison a density histogram is utilized as this is advantageous for the comparison of distributions with unequal sample sizes. Due to the large discontinuities in the density patterns when the sample size is small a density histogram can be somewhat difficult to interpret. To aid in the interpretation a kernel density estimator was utilized to enhance the visualization of the density patterns. A kernel density estimator spreads the probability mass smoothly around the observation using a kernel, allowing for a smoothing of the discontinuities in the histogram. The Gaussian kernel was adopted, details of which can be found in *(66, 68)* or Appendix D.

The distributions of ACTRA groups with the high skewness/kurtosis values are shown in Figure 14 (top) with that of the same route-period groups of SCATS (bottom). For the ACTRA groups distribution, there tends to be an outlier with a travel time roughly twice the mean value. These outliers are isolated, with significant gaps between the outlier and the next lower value. On the other hand, although the highest observed travel time is almost the same in SCATS data as the ACTRA data, the skewness and kurtosis values are lower and the mean value is higher. This is a result of the travel time values being more dispersed (towards the highest observation), with no gaps, or narrower gaps, in the distribution of the higher travel times in the corresponding groups of SCATS data.

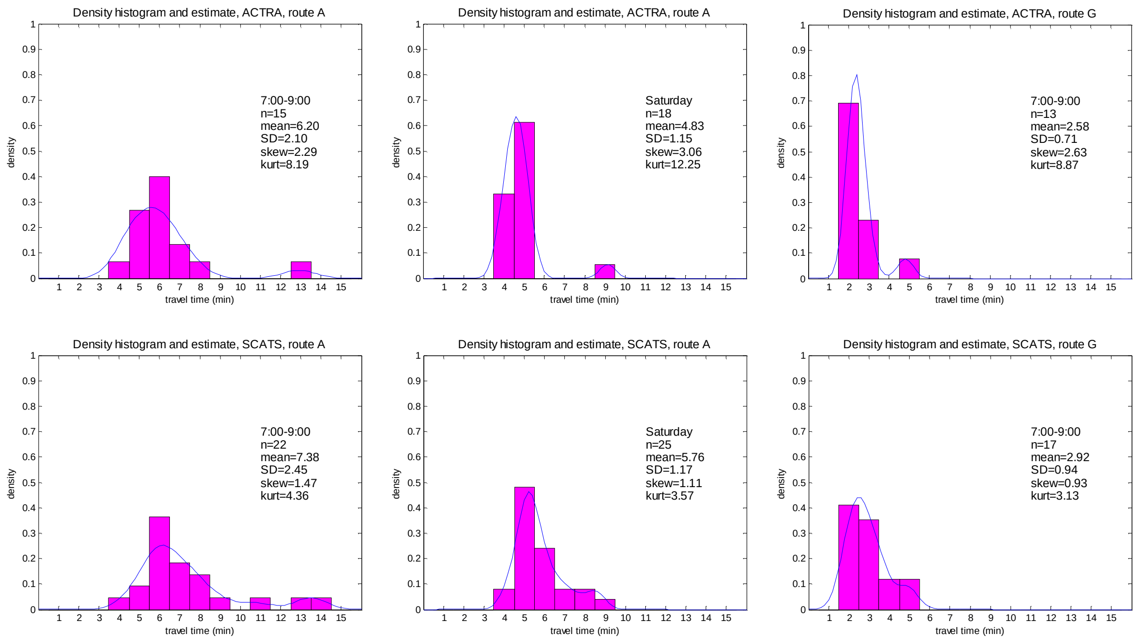


Figure 14: Travel time distribution of ACTRA groups with extremely high skewness (top) and that of the same route-period groups of SCATS (bottom)

To examine further the details of the distributions discussed above, the individual travel time data of the groups were plotted (Figure 15). The data collected on the same day are connected by a solid line and the run numbers are in chronological order. The plots of ACTRA groups (top) indicate that the individual travel time increased temporarily. However, the influence of the fixed control is seen with the travel time returning back to earlier trend and remaining stable. These plots suggest for these outlier cases that for the given demands, while some perturbations may exist ACTRA provided relatively consistent performance. On the other hand, the individual travel time of SCATS groups (bottom) continuously went up and down, potentially reflecting the real time adjustment of the control to traffic demand fluctuations. However, the average service provide by SCATS was worse for all three cases.

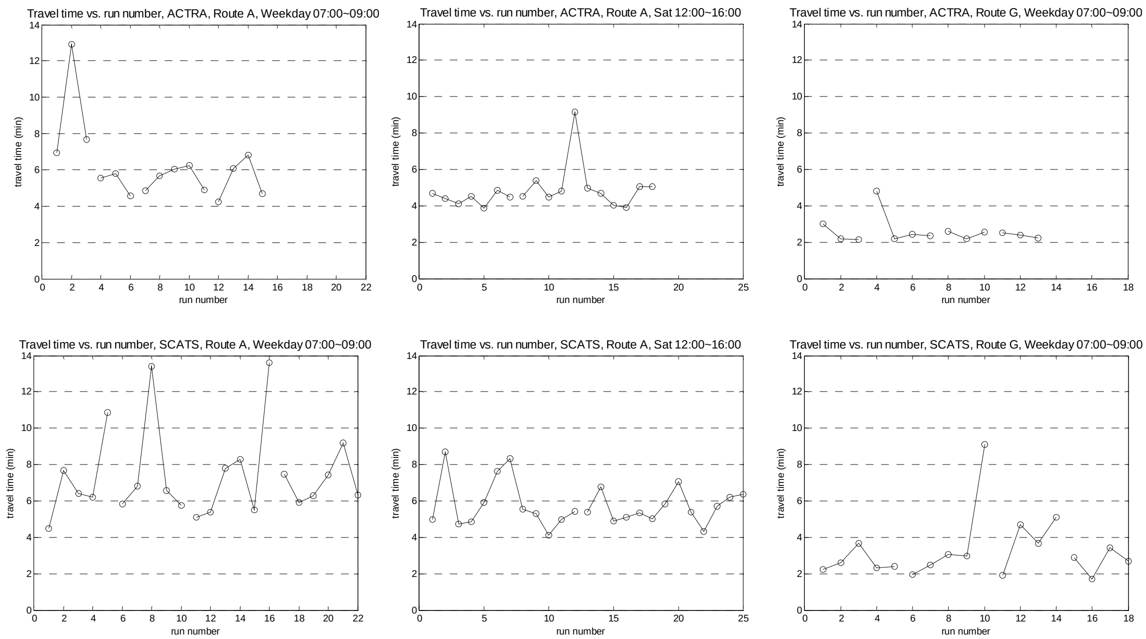


Figure 15: Individual travel time of ACTRA groups with extremely high skewness (top) and that of the same route-period groups of SCATS (bottom)

The distribution and the individual travel time data of the ACTRA group with the extremely low skewness value are presented in Figure 16 (top) with those of the same route-period group of SCATS (bottom). For this ACTRA group the two outliers that are roughly half the mean, again with a significant gap between the outliers and the majority of the data. Under ACTRA, there was again vehicle which experience a significantly different individual travel time (in this case lower), however, the travel time returned to the general trend with little overall fluctuation. This pattern may suggest for this group that the fixed control parameters are less optimal for the route and the time period. Similar to the high skewness cases, the gap in the distribution does not exist under SCATS, and the individual travel time demonstrated a higher degree of fluctuations. The overall travel time was lower than that of ACTRA, implying that the parameters of SCATS may be closer to the optimal.

Combining the high and the low skewness cases, a common characteristic of SCATS for the discussed cases is found. The adaptive feature of SCATS contributes to merging the major part of a distribution and the outlier(s) by moving the major part toward the outlier(s). As a result, the absolute value of skewness decreases, the value of kurtosis decreases, and the location of mean moves toward the outliers.

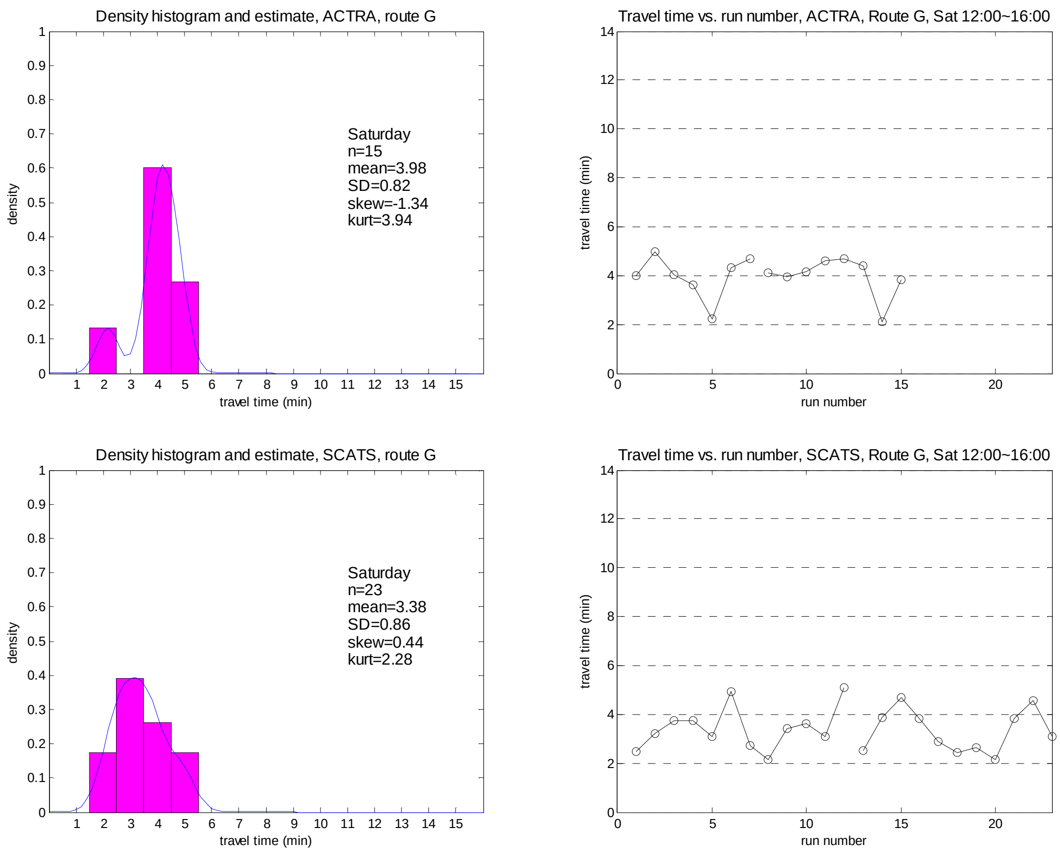


Figure 16: Distribution and individual travel time of ACTRA group with extremely low skewness (top) and those of the same route-period groups of SCATS (bottom)

Travel time distribution of groups with relatively low kurtosis values

The previous section exhibited that SCATS had a lower kurtosis values during the time periods ACTRA had unusually high values. This was accomplished by SCATS providing a higher mean travel time with travel times more distributed over the range of observations. This section compares the distribution of groups with relatively low kurtosis and mid-range skewness values under ACTRA with that of the corresponding time period and route combination groups under SCATS. An ACTRA morning peak, evening peak, and off peak group were randomly chosen from the groups with the kurtosis value of approximately two. (Recall, the kurtosis range, 1.5 to 2.5 represents the majority (about 44%) of the ACTRA data, in Figure 10). Although no consistent difference was observed between the ACTRA and SCATS skewness values, the mean and skewness consistently moved in opposite directions, that is, when the skewsness increased, the mean decreased and vice versa. Kurtosis values increased for all the three groups (Figure 17). As the distribution became more peaked, the standard deviation of the groups decreased. The individual travel time plots in Figure 18 show that travel time is slightly more consistent under SCATS for these groups.

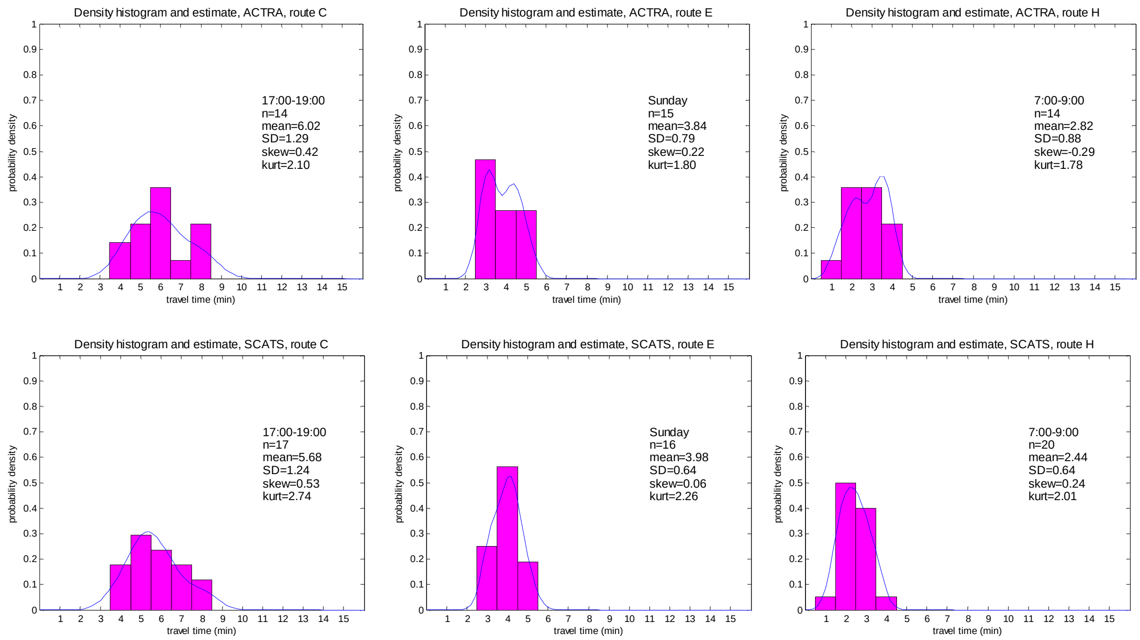


Figure 17: Travel time distribution of ACTRA groups with relatively low kurtosis (top) and that of the same route-period groups of SCATS (bottom)

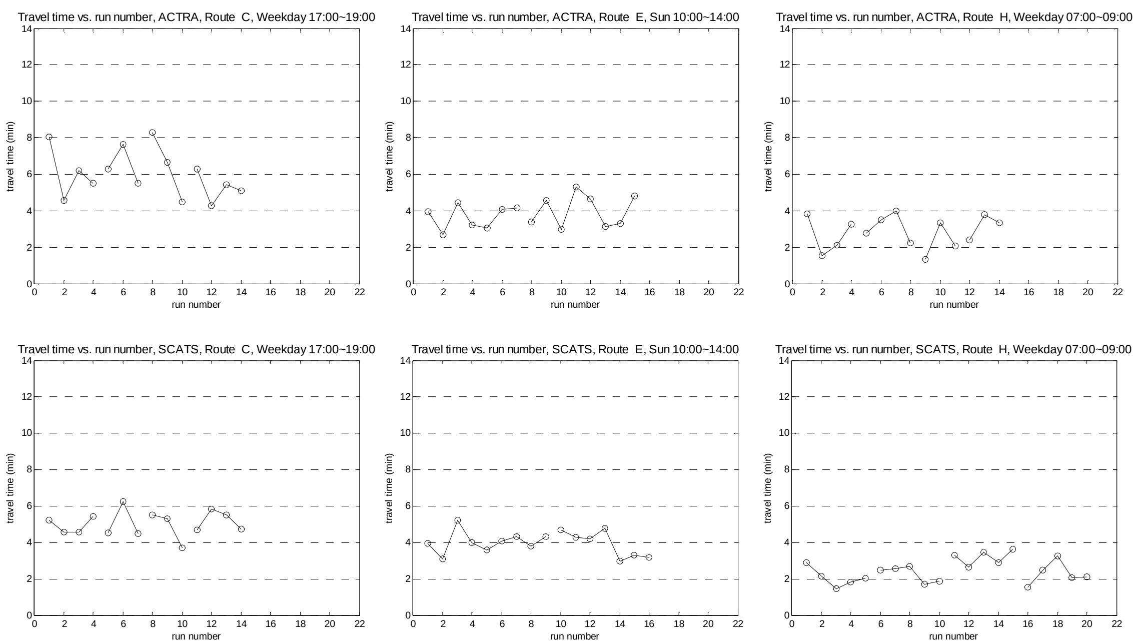


Figure 18: Individual travel time of ACTRA groups with relatively low kurtosis (top) and that of the same route-period groups of SCATS (bottom)

SCATS performance related to travel time distribution under ACTRA

The results of the previous sections may suggest that SCATS tended to decrease the peakedness of highly peaked distributions and to increase that of relatively flat distributions. Also it appeared that standard deviation changed according to this peakedness change; a more peaked distribution is less dispersed. In terms of skewness, its changing direction appeared to be opposite to the changing direction of mean. Along with these results, as skewness and kurtosis are associated in a non-linear manner as seen in Figure 13, the two shape statistics under ACTRA may be pseudo parameters that relate to the performance of SCATS. To examine this, two binary classification trees were constructed using the changes of mean and standard deviation as dependent variables and skewness and kurtosis of ACTRA group distributions as independent variables. The dependent variables (classes) for the tree models are (+) and (-), which indicate an increase and a decrease of a measure respectively. The details of the classification tree modeling are found in *(66, 67)* and Appendix E. For the tree model of mean travel time, the space generated by the independent variables is split into four regions (Figure 19 left), and for standard deviation, the space is split into three regions (Figure 19 right). The figures show the number of groups for each class in the regions with the location of ACTRA groups that are defined by their skewness and kurtosis value pair. Since the trees were pruned to avoid unnecessary complicatedness, some regions do not contain a dominant class. However, a dominant result based on either mean or standard deviation exists in both trees. When the distribution is extremely skewed to the right (region 1 in Figure 19 left), mean increased, but when it is not severely skewed and relatively peaked, mean decreased. Based on standard deviation tree results, when the distribution is right skewed and relatively flat, SCATS out-performed. Figure 20 exhibits the dominant improvement regions from mean and standard deviation tree results together (region 2 of mean tree and region 1 of standard deviation tree). Some points are located in the overlapped region, however many are located outside of the intersection. This suggests that a change of the distribution by a control system change may not lead to the same results in performance of different measures. In other words, a performance improvement based on an average measure does not always imply a performance improvement based on a reliability measure.

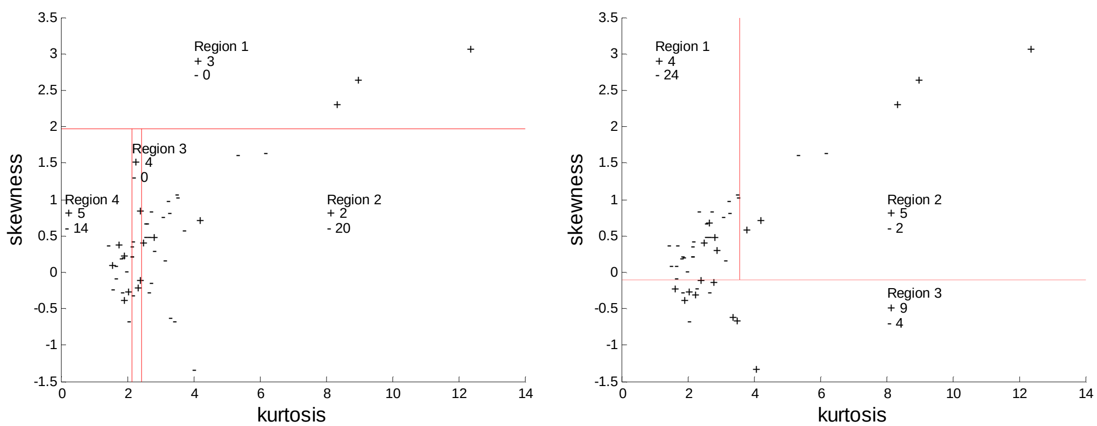


Figure 19: SCATS performance tree model with independent variable of skewness and kurtosis of ACTRA group, left: mean, right: standard deviation as dependent variable

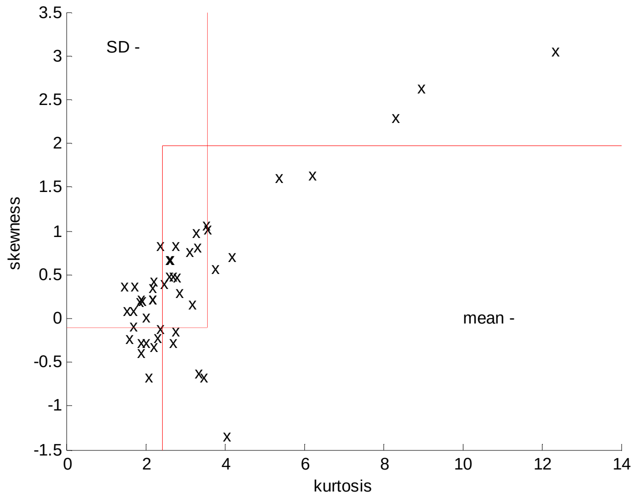


Figure 20: Dominantly improved region of mean tree superimposed with that of standard deviation tree in Figure 19

Figure 21 exhibits the points of SCATS groups (numbered) and ACTRA groups ('x') on the skewness-kurtosis plane. They are from the same regions in the mean tree (Figure 19 left). The number label is the number of the region that the group belonged to under ACTRA in the results of the mean tree (Figure 19 left). The same presentation is shown for the standard deviation tree in Figure 22. It should be noted that location of SCATS groups are close together regardless of the regions that they are from under ACTRA control. This may also indicate that the shape of the travel time distribution of the groups of SCATS is not much different in terms of skewness and kurtosis depending on the performance.

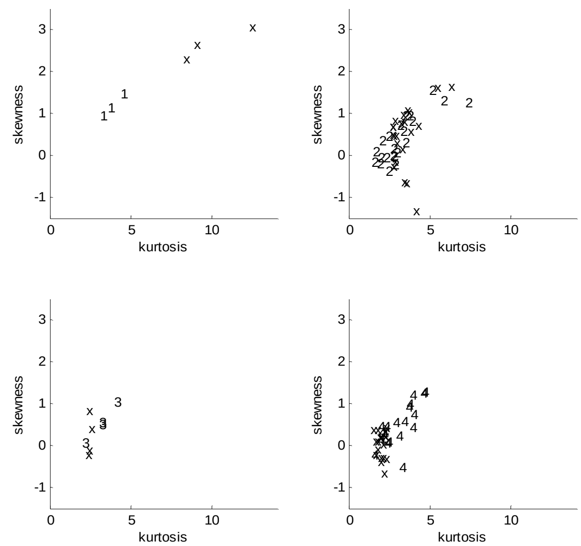


Figure 21: Location of SCATS (number by region of mean tree in Figure 19) and ACTRA ('x') groups on skewness-kurtosis plane

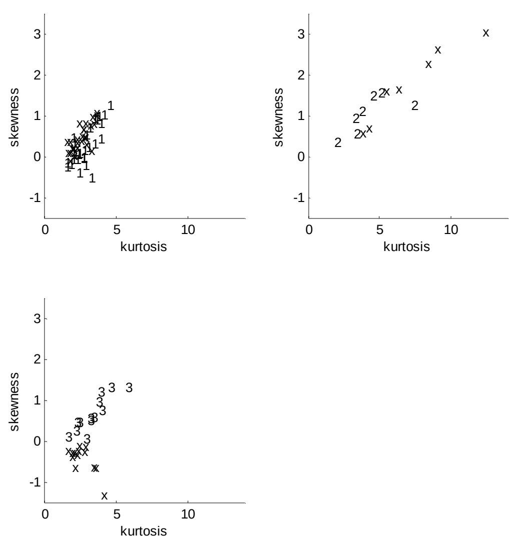


Figure 22: Location of SCATS (number by region of standard deviation tree in Figure 19 and ACTRA ('x') groups on skewness-kurtosis plane

Summary

This chapter presented an investigation of the travel time distribution under ACTRA and SCATS control on major corridors in the study area. Firstly, the travel time distribution of each time period, route, and control combination group was compared with three theoretical distributions that have been previous shown by other researchers to provide a good fit to an arterial travel time distribution: normal, log-normal, and gamma distribution. Based on K-S tests, no strong evidence was found that the travel time distributions under ACTRA and SCATS control are significantly different from the compared theoretical distributions.

Next, the shapes of travel time distributions under SCATS and ACTRA control were compared for each time period and route combination group using statistics such as standard deviation, skewness, and kurtosis. The results suggested that more extreme values of those statistics were observed in ACTRA groups. From the investigation on the relationship between the shape statistics, it was found that skewness and kurtosis had a non-linear association. On the skewness and kurtosis plot ACTRA groups with high kurtosis and extreme skewness values were identified and the distribution shape and individual travel time observations were compared with those of the corresponding SCATS groups. In the comparison, it was found that the ACTRA performance was more consistent, except for some outliers. Under SCATS, as the outlying behavior was less severe, the kurtosis value was lower and the skewness value was closer to zero. The shape of the distributions of the groups with mid-range skewness and low kurtosis values under ACTRA was also compared with that of corresponding SCATS distributions and it was found that SCATS increased kurtosis of these groups.

In either outlier groups or non-outlier groups, the change of kurtosis and skewness appeared to be consistently associated with that of standard deviation and mean, respectively. Also, SCATS tended to influence the peakedness of distributions consistently. Thus, classification tree models were constructed with the mean and standard deviation as dependent variables and skewness and kurtosis values as independent variables. The model results suggested that to some extent, the performance improvement was related to the two shape statistics of ACTRA distribution and that the combined ranges of skewness and kurtosis values for the class showing improvements were not identical for the mean and standard deviation tree. This may indicate that a before-after study for the evaluation of a new arterial control system can produce different results depending on the choice of the performance measure, for instance average travel time or a travel time reliability measure.

CHAPTER 5. RELIABILITY

Adaptive traffic control systems often require additional sensors and more advanced computing technology than time-of-day control, resulting in a more costly system installation. A more comprehensive evaluation than traditionally undertaken is needed to justify these increased costs. Conventional measures to evaluate traffic signal control have been average measures, such as average speed, travel time, delay etc. As found in the previous chapter, depending on the selected measures, the evaluation results may favor different systems. Thus, to address the need for a more comprehensive evaluation, this study explores measures that aim to quantify travel time reliability.

From the transportation system perspective, reliability is commonly defined according to the level of travel time variation or the probability that travelers will arrive at their destination within a given time. To quantify this, reliability measures are often closely associated with the width of travel time distribution, implying that estimating a reliability measure with a reasonable accuracy requires more data than estimating an average measure. Hence, to date, reliability monitoring activities have been applicable mostly to freeways equipped with traffic surveillance systems. The evaluation of traffic signal control on arterials has typically relied on test vehicle data in which the sample size is limited in most applications.

Given the above background, the main objective of this chapter is to provide a method to measure the effect of a traffic control system using reliability measures based on test vehicle data. The method is presented using the fixed route travel time data. As stated in the previous chapter, the travel time distributions (and thus reliability measures) are not readily definable on the random routes. Therefore, the analysis focuses on well defined end-to-end routes.

The following section reviews existing travel time reliability measures considered to be appropriate for this research. In the main analysis, the interrelationship and the characteristics of the measures are described. After that, a method to obtain the confidence interval of the measures for a specific route, time period, and control type combination group is presented using the bootstrap sampling that expands the test vehicle data to overcome the sample size limitation. Based on the confidence interval, the significance of the new control effect is tested and the results are discussed.

Review of travel time reliability measure

Researchers at the Texas Transportation Institute and at Cambridge Systematics categorized reliability measures into three groups: statistical range measure, buffer measure, and tardy trip indicator *(23)*. Representative measures for each category are selected for the later analysis. As seen in the literature review chapter, some measures in statistical range measure and buffer measure have a normalized form for the comparison of different-size facilities. Those normalized measures are not considered here since this study examines the performance of the compared control systems on identical roadway segments with pre-defined fixed routes.

Statistical range measures

These measures attempt to capture the size of the variation of travel time and typically sample standard deviation of travel time is incorporated in to the measure.

- Travel time window (*(23, 31)*)

The mathematical expression of this measure is mean $\pm$ standard deviation. The percentage of trips included in this window depends on the underlying travel time distribution. Under the normal distribution assumption, 68% of trips are accounted for by this measure.

- Polus' reliability measure of arterial (*(33)*)

  Polus used the reciprocal of standard deviation of travel time to measure arterial reliability.

- Range of travel time (*(30)*)

  The mathematical form is similar to travel time window. The difference is that it contains 85% of trips if assuming normal distribution. It is calculated by average travel time $\pm 1.44 \times$ standard deviation of travel time.

Buffer measures

Buffer measures attempt to present how much "buffer" time is to be allowed in a trip to make sure that travelers arrive at the destination on time given the uncertainty of traffic conditions. This concept is well related to travelers' trip decision making process.

- Planning time (*(5, 34)*)

  Planning time is the 95th percentile of travel time. This can be the planning travel time that a traveler expects to achieve on-time arrival.

- Buffer time (*(23)*)

  Buffer time is the 95th percentile travel time minus average travel time. This is the additional allotted trip time beyond the average to allow for on-time arrival in 19 cases out of 20.

Tardy trip indicators

Tardy trip indicator represents the lack of reliability of a transportation system using the proportion of trips whose travel time is longer than an acceptable threshold.

- Florida reliability statistic, on-time arrival (*(23, 28, 30)*)

  The two measures are slightly different depending on the literature but in a similar form, 100% minus the percent of trips with a travel time greater than the acceptable travel time, where the acceptable travel time is the expected travel time plus an acceptable additional travel time (e.g. 5%, 10%, 15%, and 20% of the expected travel time). 10 % is recommended as the percentage of the expected travel time, but the selecting percentage is still under experiments *(23, 30)*. Mean and median are used for the expected travel time of Florida reliability statistic and on-time arrival respectively.

Data

Grouping data by time period-route-control combinations

As in the previous chapter, the data collected under each control is categorized by relatively homogeneous groups for comparison of the reliability measures. The fixed route data are grouped into six time periods (four two-hour weekday periods and two four-hour weekend periods) and eight routes (A to H), resulting in forty eight groups for each control type. The time window of each time period is identical to that used for the previous chapter. The sample size of the groups ranges from 8 to 31 runs (Table 9).

Route characteristics

The main focus of the analysis in this chapter is the comparison of the selected measures for the fixed routes. To better understand the analysis results, the characteristics of the study area and the eight fixed routes are presented. The study area is comprised of fifteen intersections (numbered from 7 to 21 in Figure 23) on three arterials: Atlanta Road, Paces Ferry Road, and Cumberland Parkway. The majority of the systems lie on a two mile stretch of Paces Ferry Road, from the intersection of Atlanta Road and Paces Ferry Road on the west end to the intersection of Paces Ferry Road and Paces Mill Road on the east end. The west end of the study area is primarily a four-lane residential collector street (with a small strip mall on Atlanta Road) until just prior to the I-285 and Paces Ferry Road interchange, where the development character is that of office parks, shopping centers, and hotels. The east end of the study area (primarily a two-lane arterial), passes through an area with a mix of office parks, shopping, and residential uses. Route A and B capture the end-to-through movement on Paces Ferry Rd, Routes D and H capture the through movements on Cumberland Parkway, and Routes C, E, F, and G capture trips that go from Paces Ferry Road to Cumberland Parkway or from Cumberland Parkway to Paces Ferry Road. Table 10 describes the routes regarding the origin and the destination intersection, length, speed limit, the number of left turn, and the number of lanes; and Figure 24 exhibits the geographical layouts.

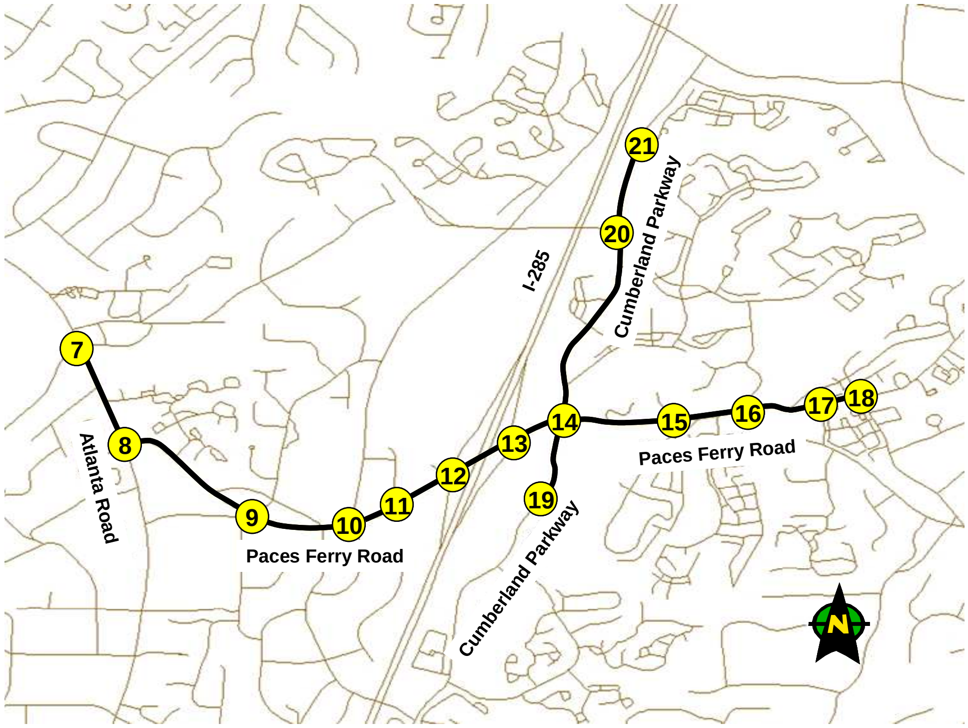


Figure 23: SCATS pilot study area intersections
Map source: Georgia Department of Transportation Highway Performance Monitoring System

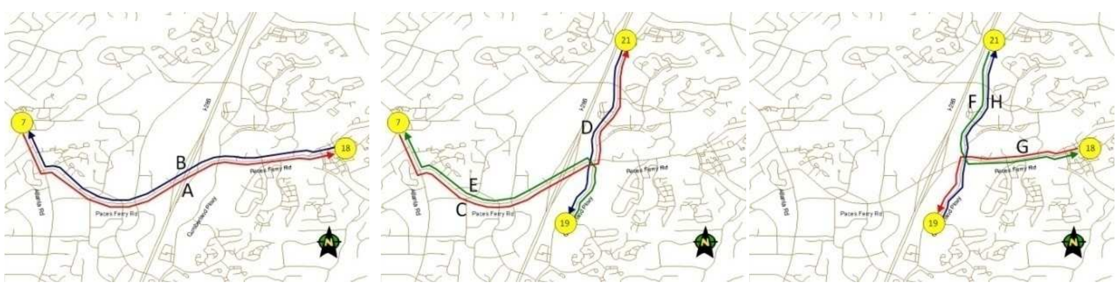


Figure 24: Fixed test vehicle routes
Map source: Georgia Department of Transportation Highway Performance Monitoring System

Table 10: Description of fixed routes

Route	Origin ID	Destin-ation ID	Length (mile)	Speed Limit (mph)	# left turn	# lane (side street ID inside parenthesis)
A	7	18	1.94	35*	1	4 lane arterial west of Boulevard Hills Rd (15), 2 lane arterial east of Boulevard Hills Rd
B	18	7	1.94	35*	0	4 lane arterial west of Overlook Pkwy (16), 2 lane arterial east of Overlook Pkwy
C	7	21	2.07	35	1	4 lane arterial
D	21	19	0.97	35	0	4 lane arterial
E	19	7	1.53	35	1	4 lane lane arterial
F	21	18	1.38	35	1	4 lane arterial west of Boulevard Hills Rd (15), 2 lane arterial east of Boulevard Hills Rd
G	18	19	0.84	35	1	4 lane arterial west of Overlook Pkwy (16), 2 lane arterial east of Overlook Pkwy
H	19	21	0.97	35	0	4 lane arterial

Note: * except on Atlanta Road between intersection 7 and intersection 8, where speed limit is 45mph

Characteristics of reliability measures

Selected measures

Representative measures from the reliability measure categories are selected for the following analysis. Standard deviation is selected to represent the statistical range measures. Both buffer measures (planning time and buffer time) are selected since they are intended to capture different aspects of the trip planning. To calculate buffer time the planning time (or 95th percentile travel time) needs to be obtained. If it is obtained from a distribution fitted to data then the standard deviation and buffer time may be numerically correlated. Therefore, planning time was not calculated from an estimated distribution but directly from data with an appropriate interpolation between the observations that encompass 95th percentile. To represent the tardy trip indicators, the percent of trips with the travel time greater than 110% of the average travel time, i.e. 100% minus the original statistic (referred to as non-ontime,) is used for consistency as a higher value of the original statistic (tardy trip indicator) implies a higher level of reliability, while for the other selected measures a higher value implies decreasing reliability. Mean travel time is also selected for comparison purpose.

Correlation between reliability measures

The scatter plots showing potential correlations between measures are shown in Figure 25, and the correlation coefficients are displayed in Table 11. Each point represents the given measure for one route-period-control data set. It is noted that both the SCATS and ACTRA data are included in the plots, as plots for each individual control strategy were developed and seen to be similar. As expected, it is seen that mean travel time is highly correlated with planning time ($r = 0.909$) because higher mean travel times indicate higher planning times. Also, as planning time is incorporated in the calculation of buffer time, the two measures are highly correlated ($r = 0.832$). The correlation of mean with standard deviation ($r = 0.563$) and buffer time ($r = 0.526$) is not as significant (although some correlations clearly still exists), implying that the average and the dispersion of travel time are less associated. This relationship may explain the negative correlation ($r = -0.436$, although it is weak) between mean and non-ontime. As mean increases, the acceptable travel time, which is a fixed percentage of the mean, also increases. However, as the rate of increase in the dispersion is less, the proportion of late arrivals decreases. Standard deviation and buffer time are likely highly correlated as they both represent the width of the distribution.

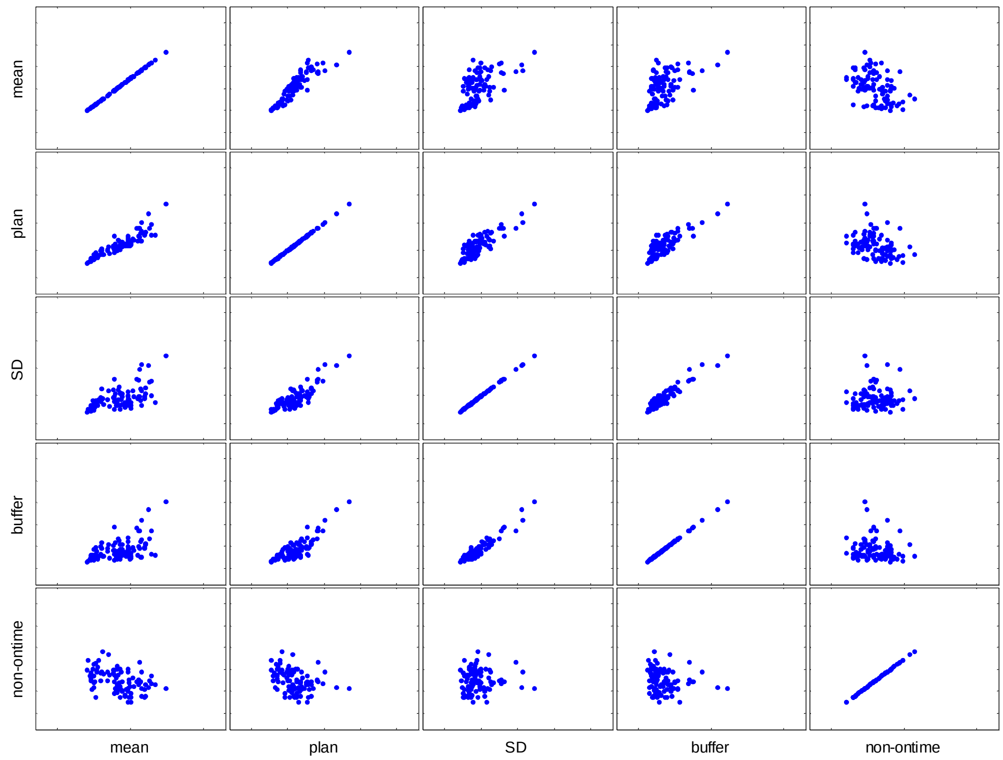


Figure 25: Scatter plots showing correlation between selected measures
Note: plan=planning time, SD=standard deviation, buffer=buffer time

Table 11: Correlation coefficient between selected measures

	Mean	Planning time	Standard deviation	Buffer time	Non-ontime
Mean	1.000	0.909	0.563	0.526	-0.436
Planning time	0.909	1.000	0.831	0.832	-0.341
Standard deviation	0.563	0.831	1.000	0.947	0.081
Buffer time	0.526	0.832	0.947	1.000	-0.116
Non-ontime	-0.436	-0.341	0.081	-0.116	1.000

Travel length and variability of travel time

The degree of correlation between mean and dispersion measures (standard deviation and buffer time) suggests that the travel time variability is not strictly proportional to the length of travel. The relationship between the variability, as indicated by standard deviation, and the travel length, as indicated mean travel time or travel distance, is displayed in Figure 26 and Figure 27 for ACTRA and SCATS data respectively. In this figure each data point is displayed according to its route identifier. The same identifiers at different locations represent the data groups of different time periods. Mean travel time is proportional to the variability only on short and simple routes (D and H). The standard deviation versus distance plot shows that the travel time of the routes that have both a left turn and the one-lane segments (A, F and G) was generally more variable, suggesting that geometric conditions or underlying signal coordination strategies may affect the variability more than the travel length in the study area.

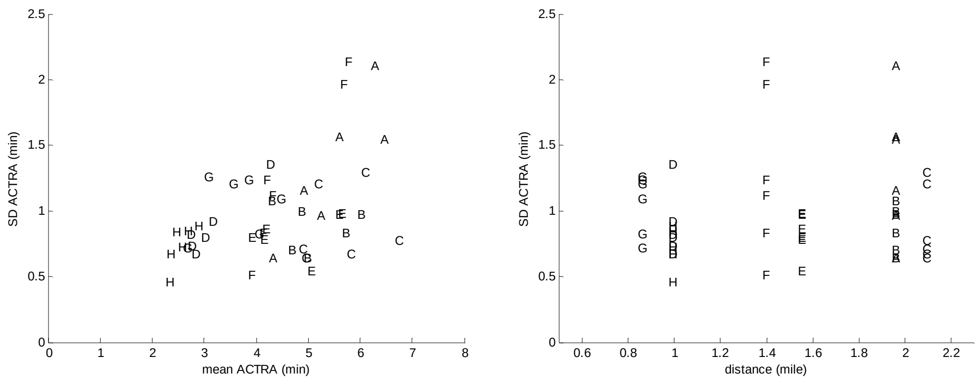


Figure 26: Standard deviation versus mean travel time (left) and travel distance (right) for ACTRA data

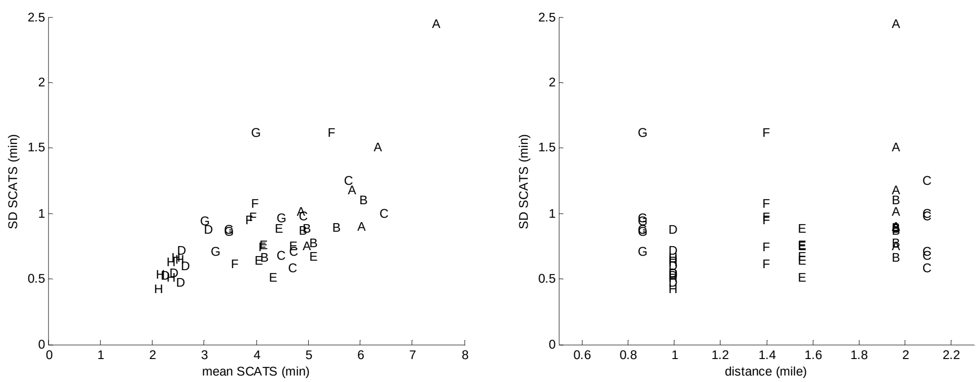


Figure 27: Standard deviation versus mean travel time (left) and travel distance (right) for SCATS data

Tardy trip indicator sensitivity to level of acceptable travel time

As seen in the previous analysis, the representative tardy trip indicator, non-ontime, does not exhibits the generally high and positive correlations seen between the other measures. To explore the impact of the control strategies on the measure different acceptable travel time cutoff percentages were tested. It is seen in this sensitivity analysis that the selected acceptable travel time can significantly impact the comparison of the control strategies. To illustrate this, the sensitivity of the non-ontime value to the acceptable travel time is obtained by applying increasing proportions (105% to 130%, increasing by 5%) to the mean of ACTRA and SCATS group data on route A, during morning off-peak (09:00~11:00). When 105% is used, SCATS shows a higher value. However, when the percentage increases over 110%, ACTRA shows higher values. In this example at 130% of travel time the SCATS measure reduces to zero. Of the 48 different period-route groups, it is seen that the tardy trip indicator identifies both strategies as superior, depending on the accepted percentage of travel time, in 28 cases. These results suggest that the value of this measure depends on the cutoff percentage. Although 10% is recommended in a previous study, the determination of the percentage is still under experiments *(23, 30)*. In addition, this measure is negatively correlated to mean, implying that a longer travel time lower this measure, which makes the interpretation difficult. Also, as this measure represents late arrival portions based on the mean location of a compared control type group, a control strategy that reduces overall travel time may be seen inferior. For these reasons, tardy trip indicator is not considered in this study.

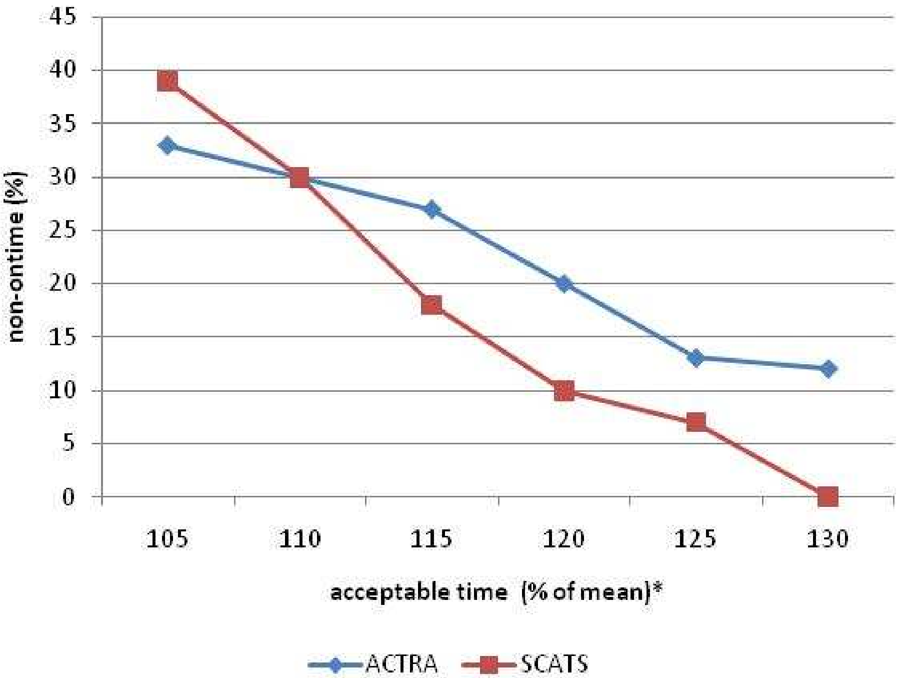


Figure 28: Sensitivity of tardy trip indicator to level of acceptable travel time
Note: * percentage applied to respective mean of ACTRA or SCATS group data

Standard deviation and buffer time

The previous analysis revealed that standard deviation and buffer time are highly correlated although they are intended to capture different aspects of the travel time distribution. For further understanding of the relationship, the two measures were evaluated and the scatter plots comparing the value of the measures under the compared control systems were obtained (Figure 29). The plots of mean and planning time are also presented for comparison purpose. In the plots, the groups with a noticeable increase or decrease of buffer time were labeled as P1, P2, P3, and P4 (highest decrease at P1 and P2; and highest increase at P3 and P4). The travel time distribution of those groups are presented by density histograms and Gaussian kernel estimator (see *(67)* or Appendix D) in Figure 30. The text inset in each histogram shows the time period, the sample size, and the values of the selected measures in minute.

Group P1 has a highly dispersed travel time distribution with an extreme outlier under ACTRA and the dispersion is significantly reduced by SCATS. The dispersion of group P2 is also relatively high under ACTRA and it also significantly reduced. The relative location of the two groups in the standard deviation and the buffer time plots depicts that standard deviation is more sensitive to the existence of an outlier. For group P3, the distribution becomes highly right-skewed under SCATS, resulting that standard deviation and buffer time increases while mean decreases. The increase of buffer time is more significant, implying that it is more sensitive to the change of skewness. This property is also illustrated in group P4. Its distribution is left-skewed under ACTRA, but is right-skewed under the SCTAS, resulting in a significant increase in buffer time.

Although standard deviation and buffer time demonstrate a difference in sensitivity to the change of the distribution, as seen in the scatter plots, the relative locations of the four groups are similar, suggesting that they captured a similar characteristic. As the travel time distribution of a majority of the groups is skewed to the right, buffer time may be quantitatively close to the statistical range measure represented by standard deviation in this study. For mean and planning time, the relative locations of the groups are different from each other and also different from those based on standard deviation and buffer time.

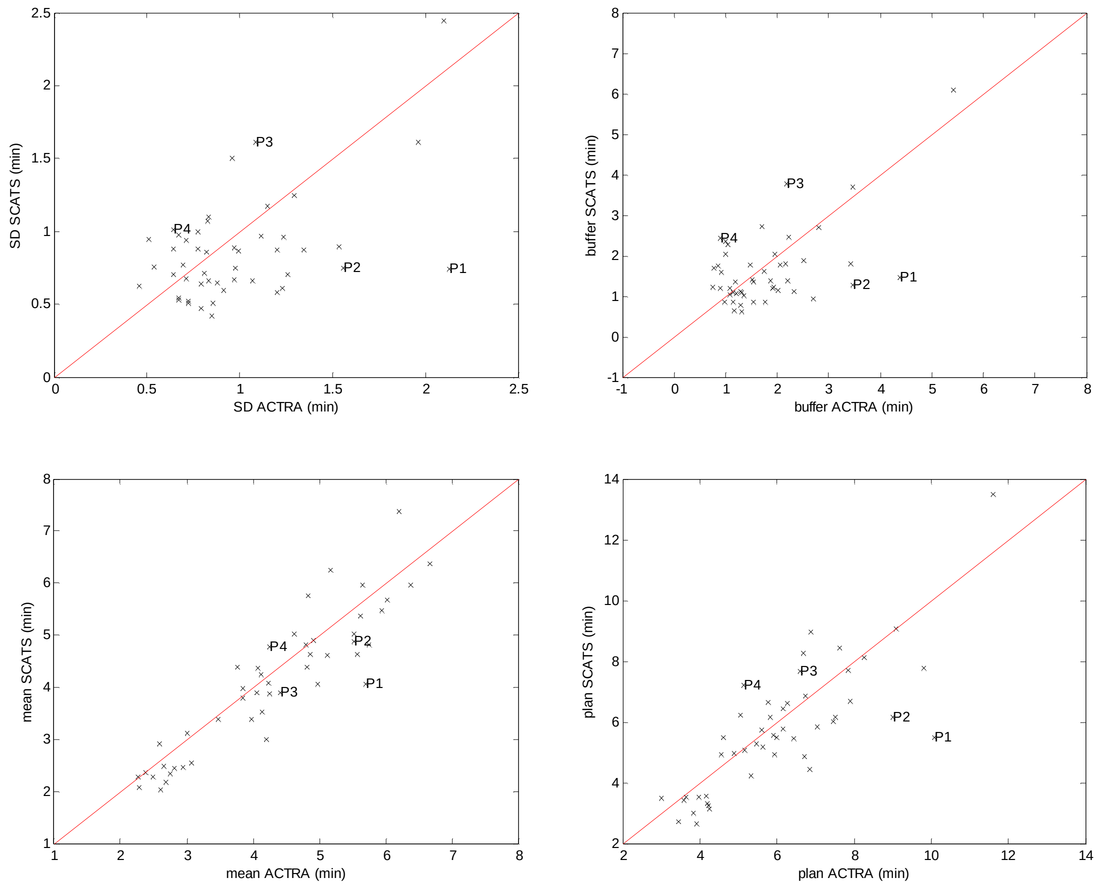


Figure 29: Standard deviation, buffer time, mean, and planning time of groups under ACTRA and SCATS

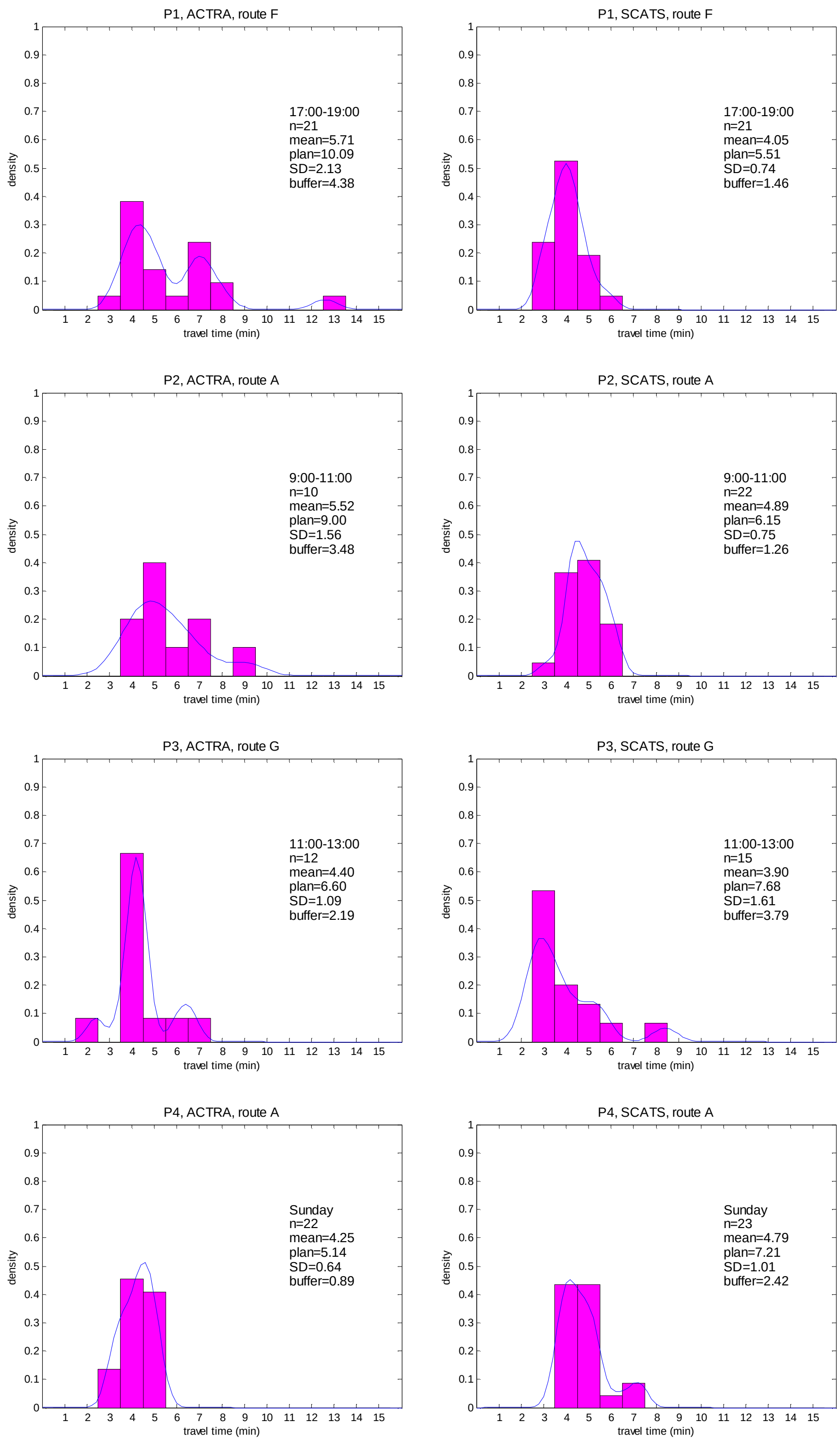


Figure 30: Travel time distribution of group P1 to P4 under ACTRA and SCATS

Non-parametric test of control effect

Method overview

The discussed measures were evaluated (estimated) for the group data in the plots of the previous sections. To statistically test the difference of the measures between the two control systems, the error variance or the confidence interval should be estimated. Traditionally, the significance of mean differences is tested using t-test that requires the normal assumption. However, as seen in the previous chapter, it is not guaranteed that the travel time data of period-route-control type groups follows a well defined parametric distribution. Under this circumstance, the estimation of error variances of selected measures using a parametric method is not readily available. Furthermore, the sample size of adopted test vehicle data is generally limited. For these reasons, the bootstrap sampling technique was used to obtain the 95 % confidence interval for each group. If the coverage of the interval from ACTRA and SCATS group data does not overlap, the increase or the decrease of the measure is statistically significant with a 5 % significance level. The theoretical basis for this method is as follows *(67)*.

The bootstrap sampling can provide an approximate $1-\alpha$ nonparametric confidence interval for a distribution parameter (θ). From an original data set with sample size n, a new sample (also sample size n) is taken by sampling with replacement. This new sample is called a bootstrap sample, which can be generated as many times as is wanted. The estimator from a bootstrap sample ($\tilde{\theta}$) describes how the estimator from the original data (θ_n) can change from sample to sample. If θ_n is a good estimate of θ, then, $\tilde{\theta}-\theta_n$ is a good estimate of $\theta_n-\theta$. A sampling distribution, $(\tilde{\theta}_1-\theta_n,\ldots,\tilde{\theta}_B-\theta_n)$ is obtained from B bootstrap samples. If the $\frac{\alpha}{2}$ and the $1-\frac{\alpha}{2}$ sample quintiles are denoted by $\tilde{\theta}(\frac{\alpha}{2})-\theta_n$ and $\tilde{\theta}(1-\frac{\alpha}{2})-\theta_n$ respectively, then,

$$P\left(\tilde{\theta}\left(\frac{\alpha}{2}\right)-\theta_n < \theta-\theta_n < \tilde{\theta}\left(1-\frac{\alpha}{2}\right)-\theta_n\right)$$

$$= P\left(\tilde{\theta}\left(\frac{\alpha}{2}\right) < \theta < \tilde{\theta}\left(1-\frac{\alpha}{2}\right)\right) \approx 1-\alpha.$$

Confidence interval comparison for route-period groups

Bootstrap sampling is conducted 5000 times for each route-period-control combination group and the confidence interval of mean, planning time, standard deviation, and buffer time was obtained. To efficiently compare the coverage of the intervals a plot was devised, in which the length of the interval of ACTRA group is the lateral width of a rectangle and the length of the interval of SCATS group is the vertical width of the rectangle. A line with a slope of 1 is drawn to aid the visual comparison of the coverage. If a rectangle dose not touch the line, the difference is statistically significant with 5% significance level. This plot shows the length of intervals and the location as well. Figure 31, Figure 32, Figure 33, and Figure 34 show the devised plots for mean, planning time, standard deviation, and buffer time, respectively. Each plot in the figures is for a route and contains six time period rectangles. The solid-line rectangles represent time periods when the compared control effect is statistically different. For those rectangles with statistical significance, time period labels are placed in the bottom-right corner.

As seen in the figures, very narrow intervals are observed only in the case of planning time. A bootstrap sample is obtained by the re-sampling process from the original sample. Considering the sample size of the original group data, the 95th percentile of planning time is significantly influenced by a small number of the observations that are close or equal to the maximum. If the original sample is left skewed or a multimodal distribution in which high-valued observations are located close together, the statistics from the generated bootstrap samples tend to be similar, resulting in a narrow confidence interval. Unlike planning time, the value of the other measures depends on all elements of a bootstrap sample, not a few observations, so the variability is higher and the interval is relatively wide. As an example, the field travel time distribution of two groups showing a narrow interval is presented in Figure 35.

The proposed statistical method assumes that the distribution of the original sample be close to that of the population. If the assumption holds, the produced intervals should be a reasonable one.

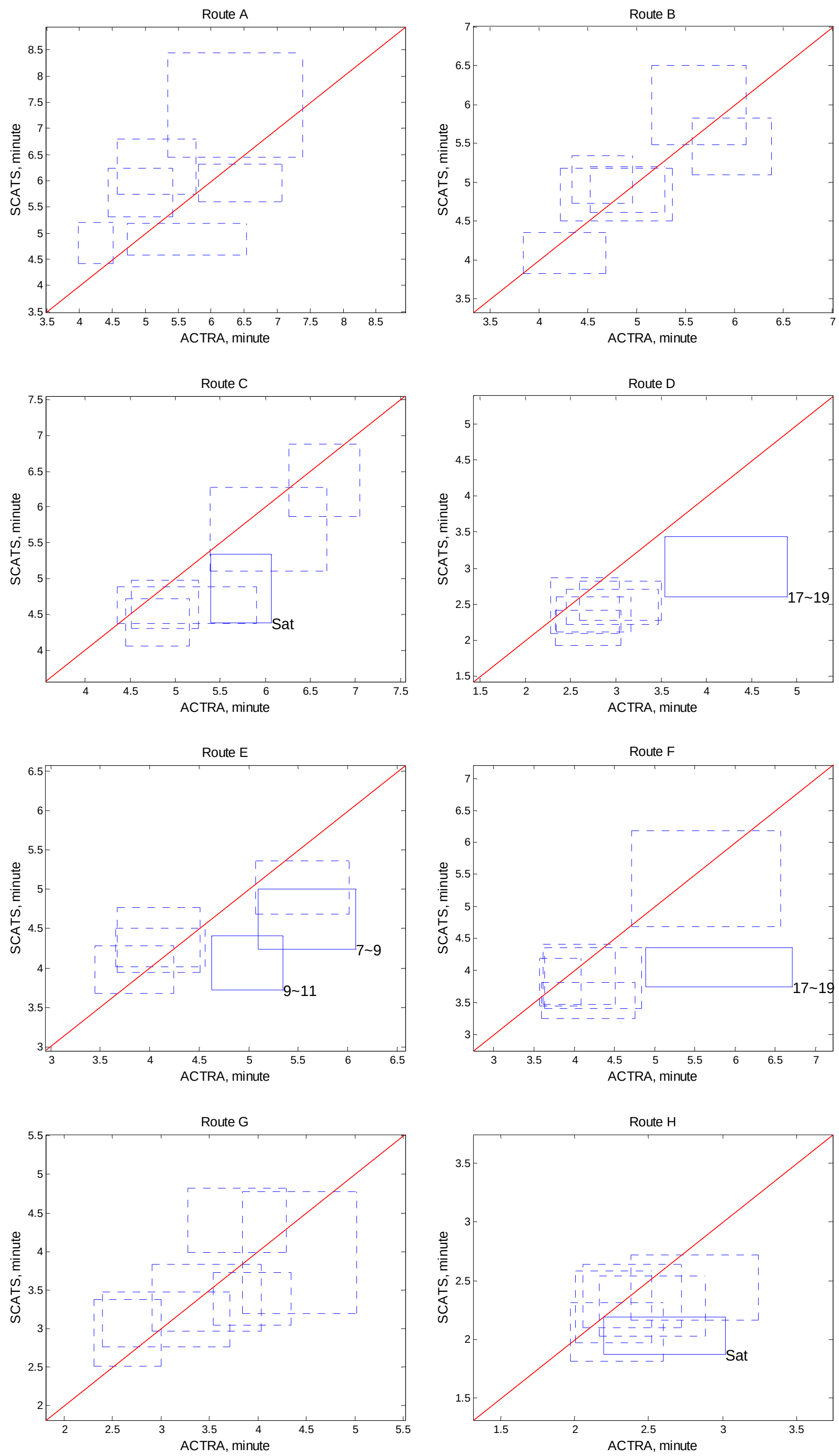


Figure 31: Comparison of confidence interval of mean

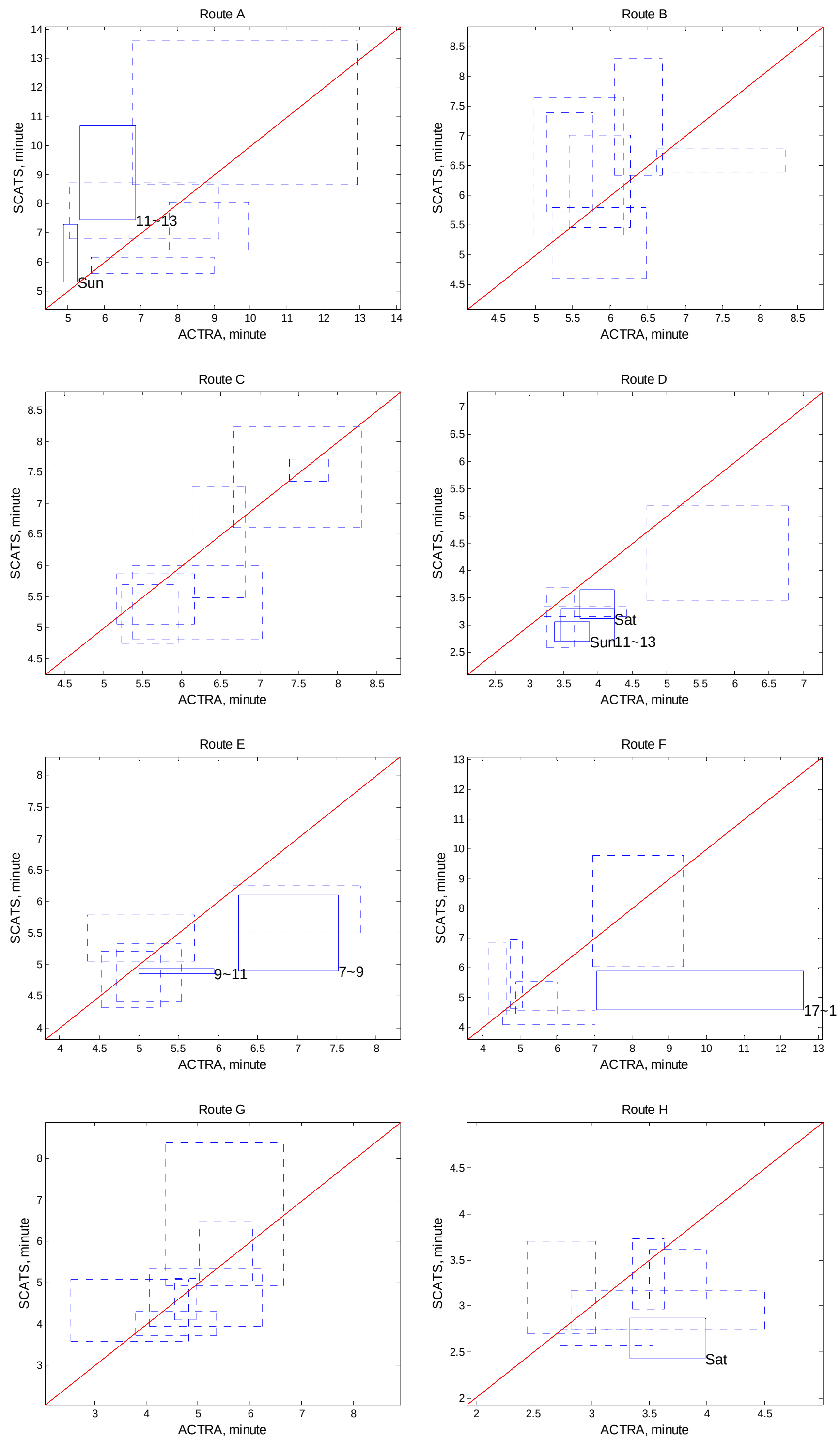


Figure 32: Comparison of confidence interval of planning time

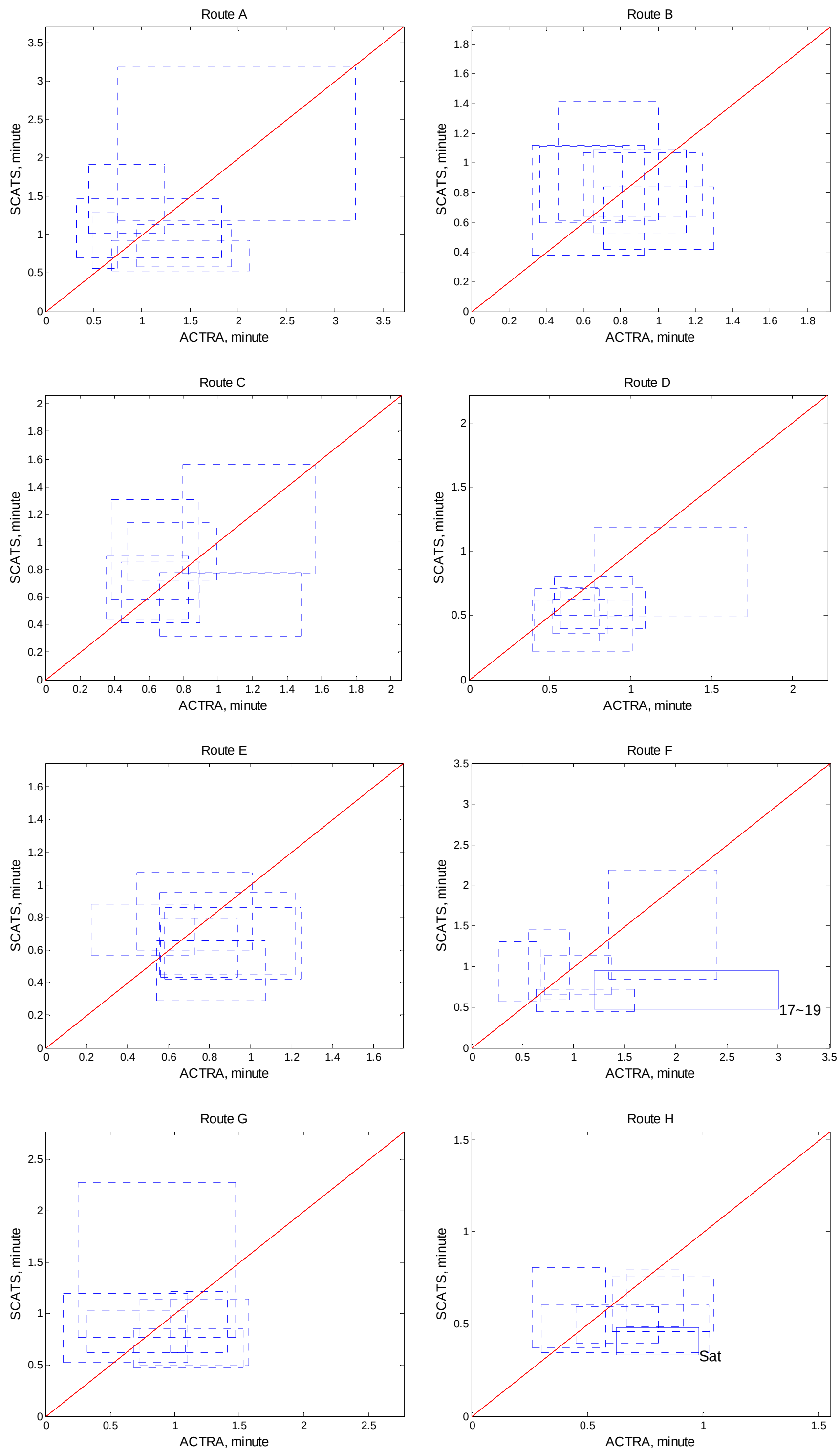


Figure 33: Comparison of confidence interval of standard deviation

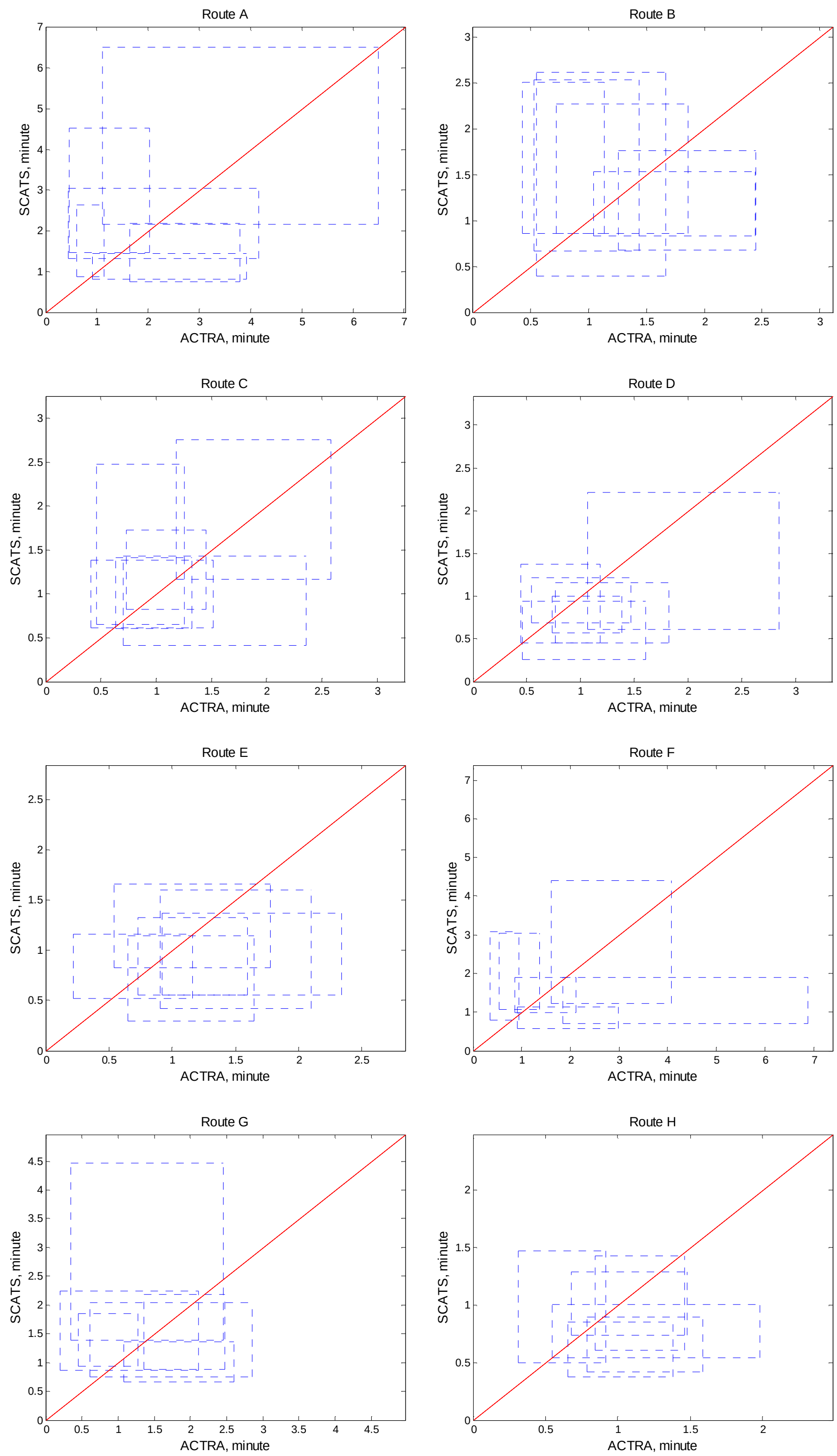


Figure 34: Comparison of confidence interval of buffer time

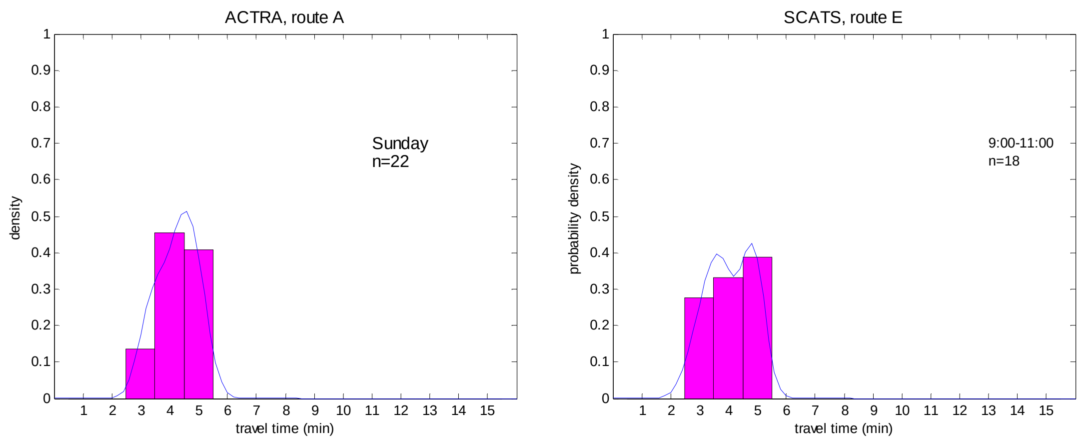


Figure 35: Example of field travel time distribution leading to a narrow confidence interval of planning time

The proposed statistical test results are summarized in Table 12. The values indicate the field data measurements. The shaded area indicates that the control type (indicated in the column header) showed a significantly lower value for the given measure in the period-route group. The bold and italic figure indicates that the mean is significantly lower in the group based on the parametric t-test, which has been adopted in most signal evaluation studies. As seen, using the bootstrap analysis the mean travel time significantly decreased in six instances under SCATS. Based on the t-test, the mean increased or decreased in seventeen groups, suggesting that the t- test is less conservative (more sensitive). Again, using the bootstrap method planning time was seen to have a statistically significant increase under SCATS control twice on route A, but decreased in seven instances on the other routes. The test results of standard deviation and buffer time were similar. As expected from the previous correlation analysis between measures, these measures do not differ notably based on behavior, even though they are intended to represent different aspects of travel time. SCATS did not statistically change the width of the distribution in most groups; only two instances of decreases in standard deviation and no instance in buffer time are seen.

Regarding the sensitivity of the statistical test of the measures, planning time showed more significantly changed groups than mean, standard deviation, and buffer time combined (Table 13). This may be because the value of planning time is determined by a smaller number of high valued observations, as discussed earlier. Thus, it may be stated that a change of planning time is generally more significant for a given distribution change. The sensitivity of the test of mean was less than planning time but greater than standard deviation and buffer time.

An important observation is that a significant increase or decrease in mean travel time between two control strategies does not always result in a significant change in reliability measures and vice versa. For two groups, only the mean changed significantly and for five groups, only reliability measure(s) changed significantly. Thus, depending on the evaluating measure, the statistical significance of a control effect can be different.

When multiple measures showed statistically significant differences, the direction of the difference tended to be consistent. For example, no group showed that ACTRA performs better (worse) based on a measure but that SCATS performs worse (better) based on other measure(s). The opposite case is not found either.

In most instances no statistical difference was seen between the SCATS and ACTRA control. Considering only the statistically significant groups, SCATS performed generally worse on Route A, but better on other routes. Route A covers the eastbound direction of Paces Ferry Road. This is the major arterial serving heavy traffic volume in the study area. It is the second longest route and passes though a left turn, a freeway junction and one-lane segments where roadside activities from adjacent land uses are frequent. Thus, it may be in the most adverse condition among the routes. Further research may be appropriate to measure the performance of SCATS in terms of characteristics of routes.

Although SCATS performed generally better on route C, D, E, and H, the number of significantly changed groups is still small based on any measure considering the total number of groups. Furthermore, route A on which SCATS was generally worse is a major one serving heavy traffic. Thus it is difficult to define one system as better than the other.

Table 12: Statistical test results of difference of measures between control systems

		A		B		C		D		E		F		G		H	
		AC	SC	AC	SC	AC	SC	AC	SC	AC	SC	AC	SC	AC	SC	AC	SC
7 ~ 9	M	6.2	7.4	5.7	6.0	6.7	6.4	2.7	2.5	5.6	***4.6***	5.6	5.4	2.6	2.9	2.8	2.4
	P	11.6	13.5	6.7	8.3	7.9	7.7	4.2	3.3	7.5	6.0	9.1	9.1	4.5	4.9	4.0	3.5
	S	2.1	2.5	0.8	1.1	0.8	1.0	0.8	0.7	1.0	0.8	2.0	1.6	0.7	0.9	0.9	0.6
	B	5.4	6.1	1.0	2.3	1.2	1.3	1.5	0.8	1.9	1.4	3.5	3.7	2.0	2.0	1.2	1.1
9 ~ 11	M	5.5	4.9	4.8	4.8	5.1	4.6	2.8	***2.3***	5.0	***4.1***	4.1	3.9	3.0	3.1	2.3	2.3
	P	9.0	6.2	6.3	6.6	7.0	5.8	3.7	3.5	6.0	4.9	5.1	6.2	5.3	4.2	3.0	3.5
	S	1.6	0.8	1.0	0.9	1.2	0.6	0.7	0.5	0.5	0.8	0.8	1.1	1.3	0.7	0.5	0.6
	B	3.5	1.3	1.5	1.8	1.9	1.2	0.9	1.2	1.0	0.9	1.0	2.3	2.3	1.1	0.8	1.2
11 ~ 13	M	***5.2***	6.3	4.9	4.9	4.9	4.6	3.0	***2.5***	4.1	4.4	4.3	3.9	4.4	3.9	2.5	2.3
	P	6.9	9.0	5.8	6.7	6.2	5.8	4.2	3.2	5.6	5.7	6.0	5.5	6.6	7.7	4.3	3.1
	S	1.0	1.5	0.6	0.9	0.6	0.7	0.8	0.5	0.8	0.9	1.1	1.0	1.1	1.6	0.7	0.5
	B	1.7	2.7	0.9	1.8	1.3	1.1	1.3	0.8	1.5	1.4	1.7	1.6	2.2	3.8	1.8	0.8
17 ~ 19	M	6.4	6.0	6.0	5.5	6.0	5.7	4.2	***3.0***	5.5	5.0	5.7	***4.1***	***3.8***	4.4	2.4	2.4
	P	9.8	7.8	7.9	6.7	8.3	8.1	6.7	4.9	7.5	6.2	10.1	5.5	5.8	6.2	3.6	3.4
	S	1.5	0.9	1.0	0.9	1.3	1.2	1.4	0.9	1.0	0.7	2.1	0.7	1.2	1.0	0.8	0.7
	B	3.4	1.8	1.9	1.2	2.2	2.5	2.5	1.9	2.0	1.2	4.4	1.5	2.1	1.8	1.2	1.1
Sat	M	***4.8***	5.8	***4.6***	5.0	5.7	***4.8***	3.1	***2.6***	4.1	4.3	3.8	3.8	4.0	***3.4***	2.6	***2.0***
	P	7.6	8.4	6.2	6.4	6.8	6.9	4.2	3.6	5.5	5.3	4.6	5.5	4.9	5.0	3.9	2.6
	S	1.2	1.2	0.7	0.8	0.7	1.0	0.9	0.6	0.9	0.5	0.5	0.9	0.8	0.9	0.9	0.4
	B	2.8	2.7	1.5	1.4	1.0	2.0	1.1	1.0	1.3	1.0	0.8	1.7	0.9	1.6	1.3	0.6
Sun	M	***4.3***	4.8	4.2	4.1	4.8	4.4	2.7	***2.2***	3.8	4.0	4.1	***3.5***	3.5	3.4	2.3	2.1
	P	5.1	7.2	6.5	5.5	5.9	5.6	3.8	3.0	5.2	5.1	6.9	4.5	5.6	5.2	3.4	2.7
	S	0.6	1.0	1.1	0.7	0.7	0.7	0.7	0.5	0.8	0.6	1.2	0.6	1.2	0.9	0.7	0.5
	B	0.9	2.4	2.2	1.4	1.1	1.2	1.2	0.9	1.3	1.1	2.7	0.9	2.2	1.8	1.2	0.7

Note: M mean, P planning time, S standard deviation, B buffer time

Table 13: Number of groups showing statistically significant performance change

	# group AC better	# group SC better	Total
Mean	0	6	6
Mean t-test	5	12	17
Plan	2	7	9
SD	0	2	2
Buffer	0	0	0

Time period combined confidence interval

This analysis aggregates the results of the time period confidence intervals for each route and is based on the route-period-control bootstrap samples previously generated. For a measure-route combination, random sampling was conducted from different time period bootstrap samples of ACTRA and SCATS and a new time period-combined sample (sample size 10,000) is generated for each control type. The sampling rate for each time period is determined based on time-of-day intersection volume count data on Paces Ferry Road reported in *(69)*. The applied rates are 0.2150, 0.1355, 0.1633, 0.2152, 0.1355, and 0.1355 for 07:00 to 09:00, 09:00 to 11:00, 11:00 to 13:00, 17:00 to 19:00, Saturday, and Sunday, respectively. Because weekend volume count data are not available, the lowest volume of weekday period (09:00 to 11:00) was assumed for weekend periods. As the sampling rate for a time period is identical for ACTRA and SCATS and the sequential order of time periods is also identical in both control-type samples, the differences of sequential elements in the new ACTRA and SCATS samples (for example *i*th element of ACTRA sample minus *i*th element of SCATS sample) can be used to construct 95% confidence interval of the difference of a measure. If this interval does not include zero, the difference of the measure for overall time periods is significant with 5% significance level.

The discussed procedure was applied to all measure-route combinations and the results are shown in Figure 36. As seen, all confidence intervals include zero, indicating that the new control effect for overall periods was not significant for any measure-route combination with 5% significance level. These results may support the results of the previous individual time period level analysis, which showed that although some route-period combinations showed a significant change of selected measures, the number of significantly changed cases is relatively small.

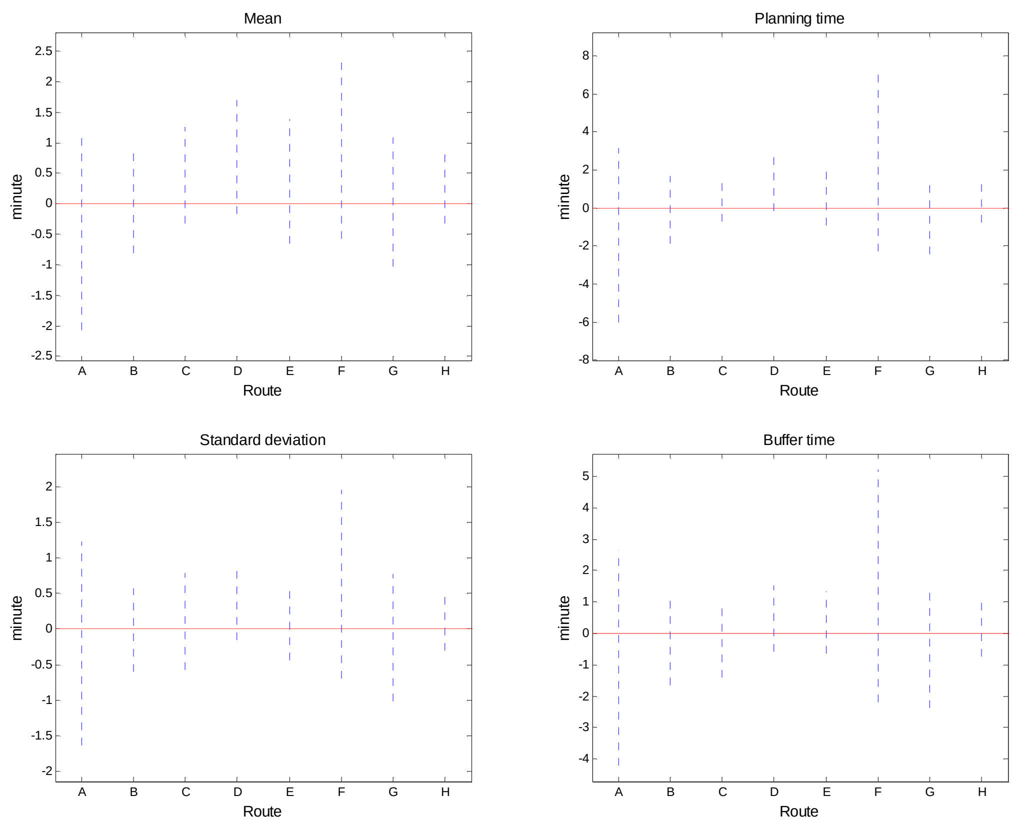


Figure 36: Confidence interval of difference of mean, planning time, standard deviation, and buffer time between ACTRA and SCATS

Summary

This chapter proposed a procedure to statistically test arterial control performance based on reliability measures. First, standard deviation, planning time, and buffer time were selected for the representative statistical range and buffer measures. Mean was also selected for comparison purposes. The tardy trip indicators were not selected because their performance is inconsistent, depending on the selected level of acceptable travel time. After the measure selection, the characteristics of the measures were examined using various scatter plots, where it was seen that standard deviation and buffer time are exhibit a similar characteristic.

Using the selected measures the performance difference between ACTRA and SCATS were statistically tested. For this, a non-parametric method using bootstrap sampling was presented. The confidence intervals for period-route groups under the compared control were obtained from the bootstrap samples. The comparison of the coverage of the intervals indicated the significance of the changes caused by the new control. In this stage, it was found that the confidence interval of planning time is narrower than that of others, likely due to the smaller number of observations contributing to this measure.

The test results showed that planning time significantly changed in nine groups, mean in six groups, standard deviation in two groups. Buffer time did not significantly change in any group. The sensitive results of planning time may be due to the discussed narrower intervals. In most groups, the change of standard deviation and buffer time were not significant. Regarding the sensitivity of the statistical test of the measures, the test of planning time may be generally more sensitive than that of others to a change in the travel time distribution.

It was observed that a significant change in the travel time mean between the control strategies does not always imply a significant change in the reliability measures and vice versa. When multiple measures of a group showed statistically significant changes, the direction of the changes was consistent.

Based on statistically significant groups, SCATS performed generally worse on Route A, which is the major arterial serving heavy traffic volume, but better on other routes. Overall, it is difficult to judge either system as superior given that for most routes and time periods, statistically different operations could not be identified.

To combine the results of confidence interval comparisons of different period-route groups, a period combined confidence interval of the difference of a measure was calculated based on the bootstrap samples previously generated and time-of-day intersection volume count data. The results showed that for all route-measure combinations, the difference was not statistically significant, supporting the results from the analysis based on individual period-route groups.

Lastly, it should be noted that the variation in a period-route-control group may not be enough to fairly represent that in the population due to sample size limitation. This may compromise the accuracy of a confidence interval generated by bootstrap sampling. In the conclusion chapter, a simulation study is discussed as future work to overcome this.

CHAPTER 6. SIDE STREE TRAFFIC PERFORMANCE

As stated, the average travel time, speed, delay, and number of stops on major corridors are the most common measures utilized to evaluated traffic control systems. For the side street performance, delays at individual intersections such as those from minor approaches and major turning approaches were investigated. For example, the intersection approach delay analysis was conducted for SCATS in Oakland County, Michigan *(36)*, Gresham, Oregon *(37)*, and Park City, Utah *(39)*; and OPAC on Route 18 in New Jersey *(40)*. However, the performance of side street traffic on a major signalized corridor, after it leaves the entering intersection, have rarely been examined, such as in Cobb County, Georgia SCATS study *(38)*.

Side street traffic competes with major street traffic for green time at arterial intersections. Because the typical arterial traffic control facilitates through (or end-to-end type route) movements, the traffic originating from minor or side streets may experience more stops along the arterial. Example vehicle paths on end-to-end type routes and from-side-street routes are illustrated in Figure 37. The paths of vehicles from side streets (represented by the dashed line) may not readily fall into the progression green band, incurring more stops than the through trips that fall into a green band (represented by the solid line). Adaptive traffic control systems attempt to effectively use time resources at intersections without necessarily relying on bandwidth optimization. Thus, the objective of this chapter is to test if an adaptive traffic control system can impact (positively or negatively) the performance of the side street originating traffic based on delays on a likely coordinated major street. A similar approach is found only in the study for SCATS in Cobb County, Georgia that examined intersection-to-intersection link travel times of side street originating traffic *(38)*. This research extends the Cobb County study by adopting corridor travel times (not on individual links) and a non-parametric model that relaxes strict assumptions needed to apply parametric models (for example, data are normally distributed).

With the aforementioned objective, this chapter evaluates an adaptive traffic control system, SCATS in Cobb County, Georgia using the random route data discussed in Chapter 3. As stated in Chapter 3, a test vehicle routing method, referred to as random route, was developed to capture the corridor travel time of the traffic from minor side streets. To test the significance of the control effect, binary regression tree models are developed to estimate the travel time on the random routes, with independent variables control types, time periods, and route geometric conditions. A major advantage of the binary tree over other non-parametric models is its interpretability *(66)*. A binary tree model partitions the dependent variable region into two regions recursively to decrease a heterogeneity measure. Each partitioning is conducted by selecting the split independent variable and split point that most decreases the measure. Therefore, the tree structure visually shows which variable is more important to estimate travel time. If the control type is selected as a split variable for any sub-tree (through a cross-validation procedure), it can be interpreted as a statistically significant variable to estimate travel time under the circumstance associated with that the sub-tree. Additional detail on the development and interpretation of binary tree analysis is present later in this chapter

This chapter is organized as follows. First, mean travel speed on the random routes and fixed routes are compared to determine if the random routes capture a different aspect of corridor travel time than the fixed routing. Then, the binary tree model framework, input variables, and sample size are presented. Finally, the developed tree model results are presented and discussed.

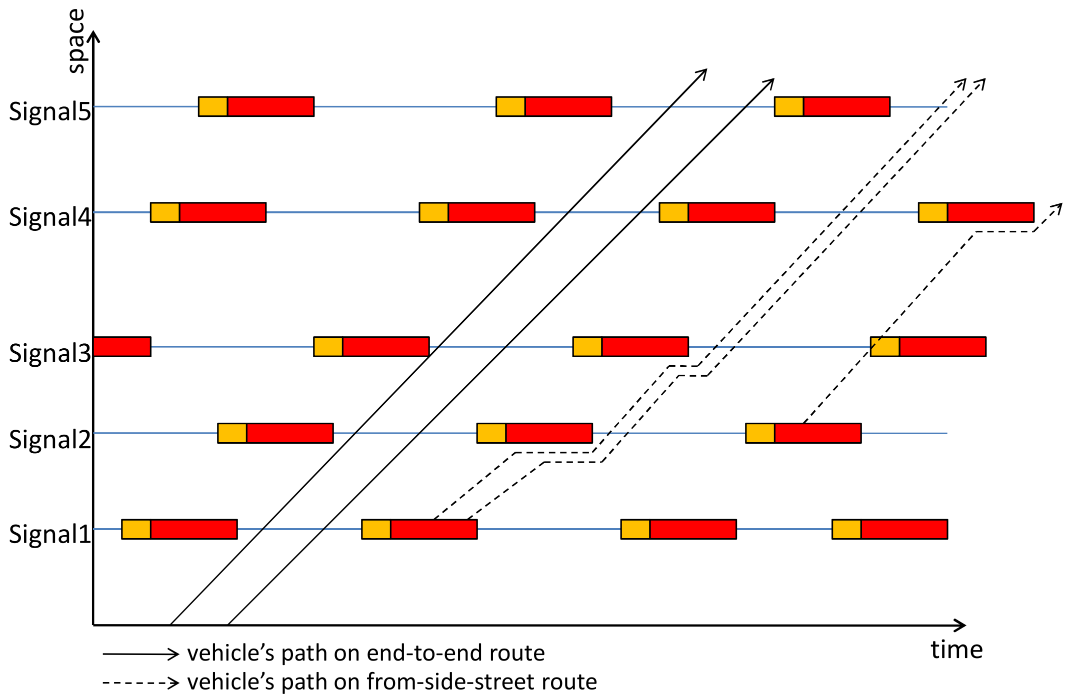


Figure 37: Example of vehicles' path and traffic signals on time-space diagram

Mean speed on random and fixed routes

Arterial service quality is commonly measured using mean speed *(47)*. For each time period Figure 38 displays the space mean speed on eastbound random routes, fixed route A, westbound random routes, and fixed route B. The speeds were calculated in such a way that aggregated total distance was divided by aggregated total travel time. For the random route data collection test vehicle runs originate only from minor side streets, excluding origination from major roads, i.e. Atlanta Road, Cumberland parkway and the I-285 exit ramps. The sample size of the random route groups ranges from 10 to 35 runs and that of the fixed route A and B ranges 9 to 31 runs (see Table 9 in Chapter 4). As the travel time on a random route includes the turning delay at the destination intersection, which is generally higher than that of through movement, the travel time on the last intersection-to-intersection segment is excluded. As discussed in Chapter 3 random routes were defined on Paces Ferry Road randomly, covering both the eastbound and westbound directions of travel. Fixed route A covers Paces Ferry Road eastbound and fixed route B covers Paces Ferry Road westbound. Thus, in Figure 38 the service quality on the random and fixed routes are subdivided into similar conditions (i.e. time period and direction). Under ACTRA, the speed on random routes was generally lower than that on fixed routes, with exceptions in the PM peak. Under SCATS, the speed of random routes versus fixed routes was more mixed. These results imply that the ACTRA timing strategy did not serve the local traffic as well as the through traffic, while the SCATS provided more consistent service between local and through traffic. These results suggest that ACTRA was more effective for the signal coordination, which is the main objective of semi-actuated coordinated control, and that the compared control systems may have treated side street traffic in different ways. Also, this finding supports that the developed random routing method was effective in identify the impact of the signal strategy on local traffic.

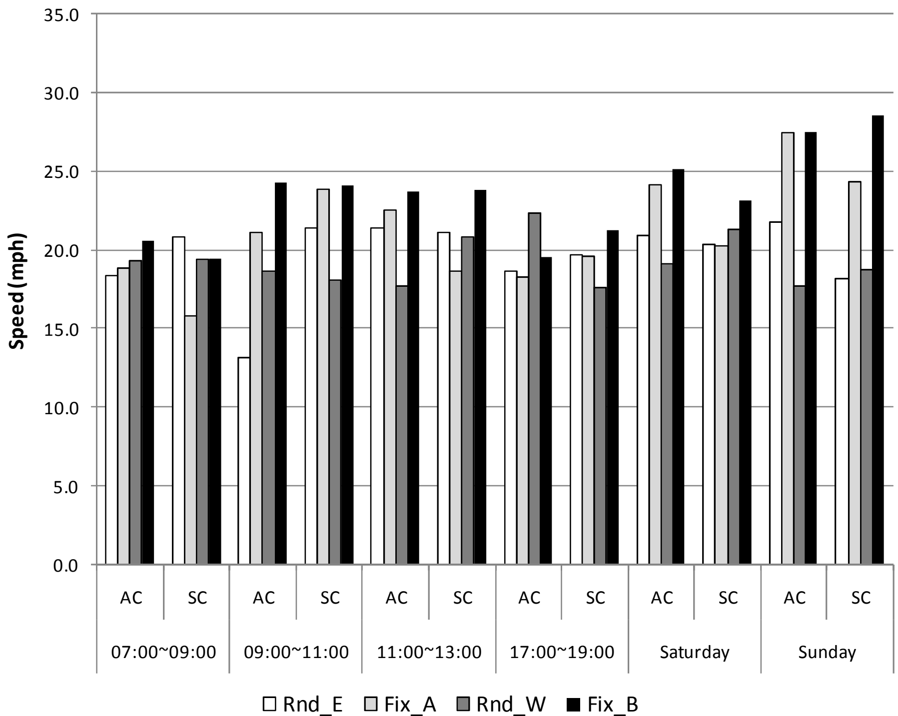


Figure 38: Mean speed on random and fixed routes

Note: AC=ACTRA, SC=SCATS, Rnd_E= random routes eastbound, Rnd_W= random routes westbound, Fix_A=fixed route A, Fix_B=fixed route B

Background of regression tree model

Linear regression models assume that the collected data follow a normal distribution. As seen in Chapter 4, it is not guaranteed that collected arterial travel time data follow a well defined parametric distribution. Non-parametric tree models have been developed to overcome this, and this research adopts the binary regression tree model. A binary tree model partitions the dependent variable domain into two regions recursively to decrease a heterogeneity measure in each region. Each partitioning is conducted by selecting the split independent variable and split point that most decreases the heterogeneity measure, usually residual sum of squares in a regression tree *(66)*. A major advantage of the recursive tree is its interpretability. With high dimensional inputs, the mechanism of the association between the response and the explanatory variables are difficult to be seen in other non-parametric models. However the tree model shows it in recursive splitting structure that is relatively easy to follow. Details of building tree model and selecting the optimal size of tree are discussed in the next section.

Tree building

This section follows the notations and discussion from *(66)*. Suppose that the data under investigation consists of p input variables and a response (dependent variable) for each of N observations, i.e. $(x_i, y_i)\ for\ i = 1,2, \dots, N, with\ x_i = (x_{i1}, x_{i2}, \dots, x_{ip})$. Also suppose that the tree model has M regions: $R_1, R_2, \dots, R_M$, and that the estimated response in each region is a constant, C_m. Then, the model is

$f(x) = \sum_{m=1}^{M} C_m I(x \epsilon R_m)$, where $I(\quad) = 1$ only when the inside argument is true.

If the heterogeneity criterion is the residual sum of squares, $\sum\left(y_i - f(x_i)\right)^2$, the best $\widehat{C_m}$ is the average of the response, that is

$\widehat{C_m} = ave(y_i | x_i \epsilon R_m)$.

For all of the data, consider a split variable j and point s, and define the pair of half planes,

$R_1(j,s) = \{X | X_j \le s\}\ and\ R_2(j,s) = \{X | X_j > s\}$.

The split variable j and point s can be obtained by solving

$min_{j,s}[min_{C_1} \sum_{x_i \in R_1(j,s)} (y_i - c_1)^2 + min_{C_2} \sum_{x_i \in R_2(j,s)} (y_i - c_2)^2]$.

For any selection of j and s, the minimization of inside [ ] is solved by

$\widehat{C_1} = ave(y_i | x_i \in R_1(j,s))\ and\ \widehat{C_2} = ave(y_i | x_i \in R_2(j,s))$.

For each split variable, the split point s can be determined quickly and thus by scanning through all the input variables, solving for the best pair (j,s) is feasible. After finding the best split, the data are partitioned into the two resulting regions (child nodes) and this splitting process is repeated at the child nodes.

Tree pruning

Obviously a very large tree may overfit the data, while a small tree may fail to capture an important structure in the data. The tree size is a parameter that controls the complexity of the model. To determine the size, this study followed the procedure in *(66)*. First, by repeating the split, grow a large tree (referred to as T_0) so that a certain minimum node size (minimum number of observations in a final node) is reached. Then, this tree is pruned until the tree that minimizes the "cost-complexity criterion" is found. Define a sub-tree T that can be obtained by pruning the original full tree T_0. Let the index for terminal nodes be m, and the node m represents region R_m. Let |T| be the number of terminal nodes in T. The estimated response in R_m, $\widehat{C_m}$ can be written as $\widehat{C_m} = \frac{1}{N_m}\sum_{x_i \in R_m} y_i$. Then, the cost-complexity criterion, $C_\alpha(T)$ can be defined as

$$C_\alpha(T) = \sum_{m=1}^{|T|} \sum_{x_i \in R_m} (y_i - \widehat{C_m})^2 + \alpha|T|.$$

As seen, the tuning parameter α relates to the trade-off between tree size and model's goodness of fit to the data. A large value of α results in a smaller size tree T_α and α = 0 results in the maximum sized tree, or the full tree T_0. For each value of α, it can be shown that there is a unique smallest sub-tree that minimizes $C_\alpha(T)$ *(66, 70)*. The estimation of α can be achieved by K-fold cross-validation, which determines the value of $\hat{\alpha}$ that minimizes the cross-validated residual sum of squares. The discussed pruning process is analogous to the step-wise process in variable selection of multiple regression models *(70)*. Thus, split variables in the final tree can be considered statistically significant.

The most widely used method for estimating prediction error of a model is cross-validation. The model parameters are determined by a training data set and the prediction error is estimated by applying the estimated model to an independent data set. In practice, often the size of available data is not large enough to split them into the training set and the validation set. To overcome this, K-fold cross validation is used *(66)*. The procedure splits the data into K roughly equal sized parts. For the k-th part, the model parameters are estimated by the other K-1 parts of the data, and prediction error is calculated when the model predicts the k-th part of the data. This procedure is conducted for k=1, 2, .. ,K and the resulting estimates of prediction error are combined. Suppose that each observation in the data is randomly assigned to one of K parts and that the fitted model using K-1 parts of the data is $\hat{f}^{-k}(x)$. Then, the cross-validated residual sum of squares, CV is $CV = \sum_{i=1}^{N}\left(y_i - \hat{f}^{-k(i)}(x_i)\right)^2$,

where, N is the number of observations in the data and k(i) is the assigned part (one of 1, 2, .. , K) of observation i. A typical choice of K is 5 or 10. If K=N, the case is referred to as "leave-one-out" cross-validation. With the tuning parameter α, the fitted model using K-1 parts of the data is $\hat{f}^{-k}(x, \alpha)$. Then, the cross-validated residual sum of squares at a value of α, CV(α) becomes

$$CV(\alpha) = \sum_{i=1}^{N}\left(y_i - \hat{f}^{-k(i)}(x_i, \alpha)\right)^2.$$

This function provides an estimate of the prediction error curve and the value of $\hat{\alpha}$ minimizing this function can be determined.

Application of binary tree model to random route data

For the full data set and also for each time period group data subset, the discussed tree building and pruning were conducted using RPART routine of R 2.9.0. Separate modeling by each time period was conducted to allow for a convenient comparison to the time period based results in the previous fixed route analysis. However, it is noted that the individual time period analysis is not necessarily warranted from the tree analysis of the full data set.

To decrease the cost complexity criterion, each split must decrease overall sum of squares error by at least α. The role of α is played by the parameter cp in R, which is defined as α divided by sum of squares error in the root node (a tree with no branch) *(71)*. Every split must decrease overall sum of squares error by at least cp multiplied by sum of squares error in the root node. Default RPART control parameters were used except for the initial value of cp that was set to a small value, 0.001 to grow a full tree. 10-fold cross-validation (K=10) was adopted to determine the optimal value of cp. 10-fold cross-validation was found to be sufficient in RPART literature *(70)*.

Input variable and sample size

For the tree model, travel time (in minute) collected on the random routes was used as the dependent variable; and control system, travel length, number of intersections passed, turning direction at origin intersection, turning direction at destination intersection, time period, and number of driveways (both sides of road) on one-lane segments are used as the independent variables. Presumably, time period, travel length, number of intersections passed, and turning direction at destination intersection are closely associated with travel time. Turning direction at origin intersection may relate to a possible travel time difference for side street originating travel because a vehicle entering Paces Ferry Road by left turn will be positioned differently regarding the coordination green band. The number of driveways on one-lane segments is adopted because as discussed in the previous chapter, the I-285 east part of Paces Ferry Road consists of one-lane segments, where frequent traffic from and to the adjacent land uses produces friction to traffic on the travel lane. As seen in Figure 39, three driveways are located from Paces Mill Road (intersection ID 18) to Overlook Parkway (16) on Paces Ferry Road west bound and five driveways from Boulevard Hills Road (15) to Paces Mill Road (18) on the east bound. The independent variables are summarized in Table 14.

Table 14: Independent variables in tree model

Variable code	Representing variable, value set
cntl	Control system, A=ACTRA, S=SCATS
len	Travel length in mile (min 0.23, max 1.54)
N_int	Number of intersections passed by test vehicle (min 2, max 8)
f_turn	Turn direction at origin intersection, R=right turn, L=left turn
t_turn	Turn direction at destination intersection, R=right turn, L=left turn
N_drv	Number of driveways on one-lane segments of traveled route (min 0, max 8)
Time period	1=7:00~9:00, 2=9:00~11:00, 3=11:00~13:00, 4=17:00~19:00 5=Sat, 6=Sun

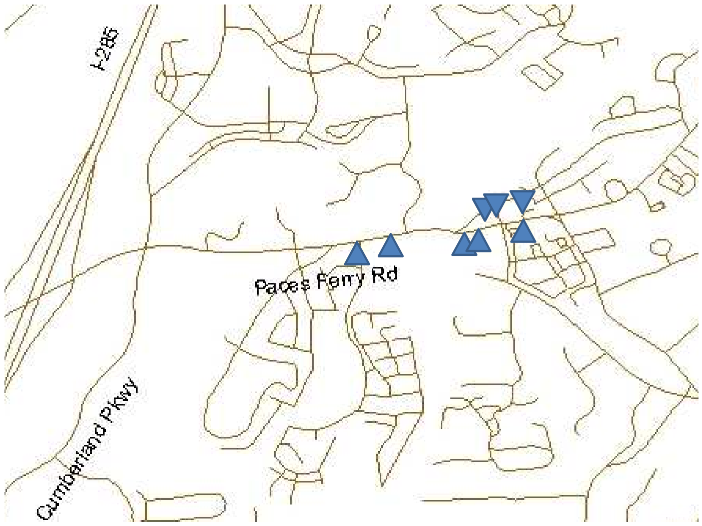


Figure 39: Location of driveway on one-lane segments on Paces Ferry Road

Table 15 shows the sample size of combined total and time period groups of the random route data.

Table 15: Sample size of random route data for tree model (unit: run)

Time period		Control system		Total
		ACTRA	SCATS	
Weekday	07:00~09:00	41	47	88
	09:00~11:00	24	53	77
	11:00~13:00	28	68	96
	17:00~17:00	23	47	70
Weekend	12:00~16:00	39	30	69
	10:00~14:00	34	27	61
Total		189	272	461

Results

Figure 40 to Figure 46 show the final trees and their R-square values for the model of the entire random route data and the models of the time period groups of 07:00~09:00 to Sunday. The top portion of the figures shows the tree structure. The numbers under the split variables are the sequential split numbers that help understand model accuracy improvements in the R-square graph at the bottom. The middle portion of each figure gives the average travel time, number of observations, and box plot showing the data distribution in final nodes. In bottom left panels, the solid line represents the R-square value calculated without cross-validation, which is referred to as the Apparent R-square and the dashed line represents the value calculated with cross-validation, which is referred to as the X relative R-square. Apparent R-square is a measure of training error and X relative R-square is that of prediction error. It should be noted that before a tree begins splitting (e.g. a tree consisting of only the root node), the cross-validated residual sum of squares is generally larger than the total sum of squares. This makes X relative R-square negative, which is observed in all tree model results, because R square is calculated by the equation below.

$$R^2 = 1 - \frac{\sum_i^N \left(y_i - f(y_i)\right)^2}{\sum_i^N (y_i - \bar{y})^2},$$

where, $\bar{y} = \frac{\sum_i^N y_i}{N}$ and $f()$ is model estimate.

X relative error in bottom right panels shows a prediction error measure that is one minus X relative R-square.

Results of tree model with full data set

Figure 40 displays the results of tree model using entire random route data as the input (see Appendix F for tabulated results). The apparent error is around 0.6 and the X relative error is around 0.4. As seen the bottom left panel, the X relative error reduces until 5th split and the later splits do not contribute significantly to model accuracy improvements. Number of intersections passed, travel length, turn type at destination intersection, and time period are involved variables in those splits. It should be noted that some splits occur at the same time at a given complexity parameter (see Appendix F). For example, 4th and 5th split occur at the same time and the R-square graph shows the combined accuracy improvement at the 5th split. The control variable appears at the 12th split. The 10th, 11th, and 12th split altogether improve apparent R-square and X relative R-square by about 0.036 and 0.012 respectively, implying that control type variable is not an essential factor to estimate travel time on random routes. Time period (tod) is one of the main variables that improve model accuracy. For comparison with the results from fixed route data analysis in the previous chapter, tree models are constructed for time period groups and the results are discussed in the following section.

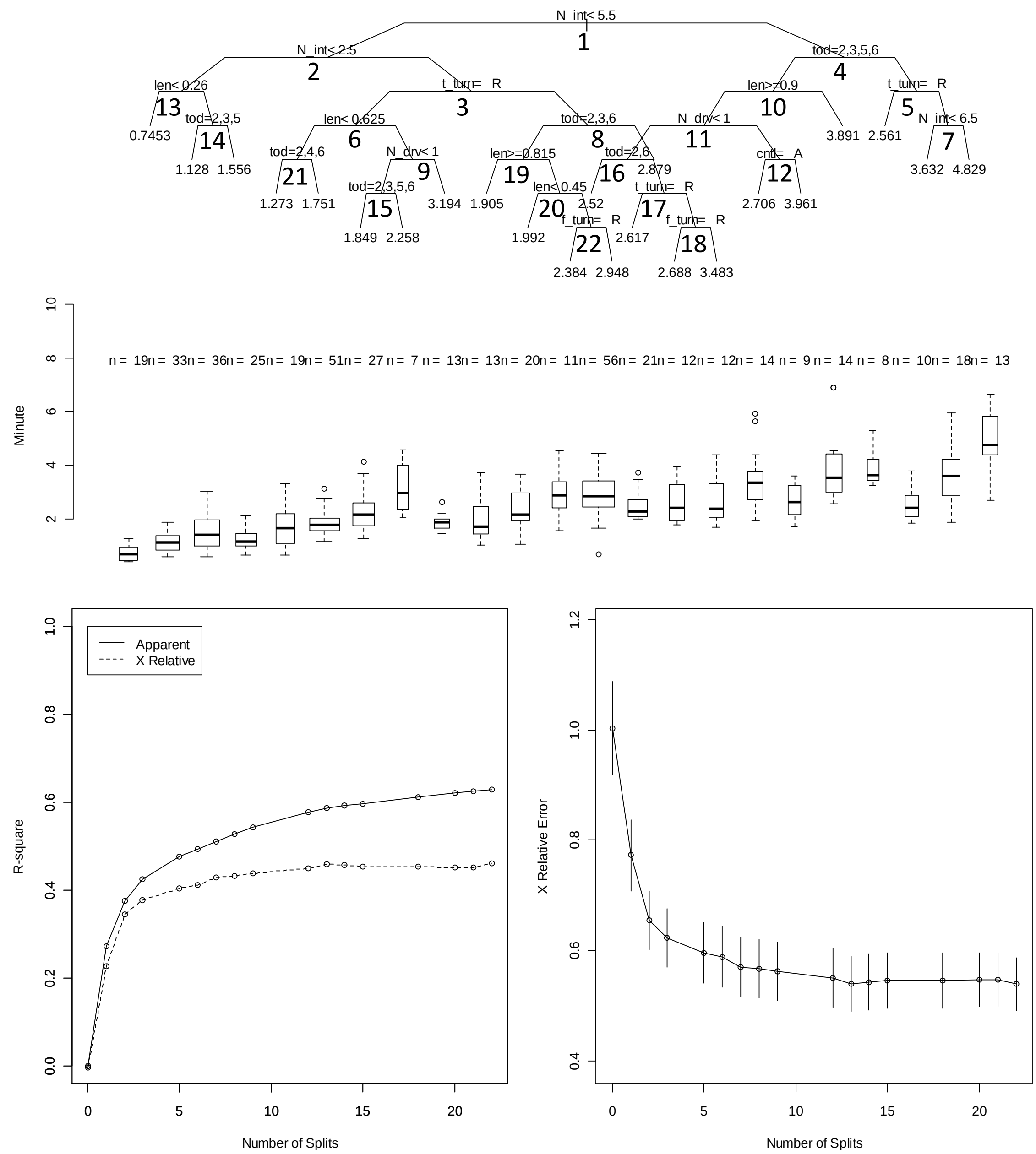


Figure 40: Tree model for full random route data set

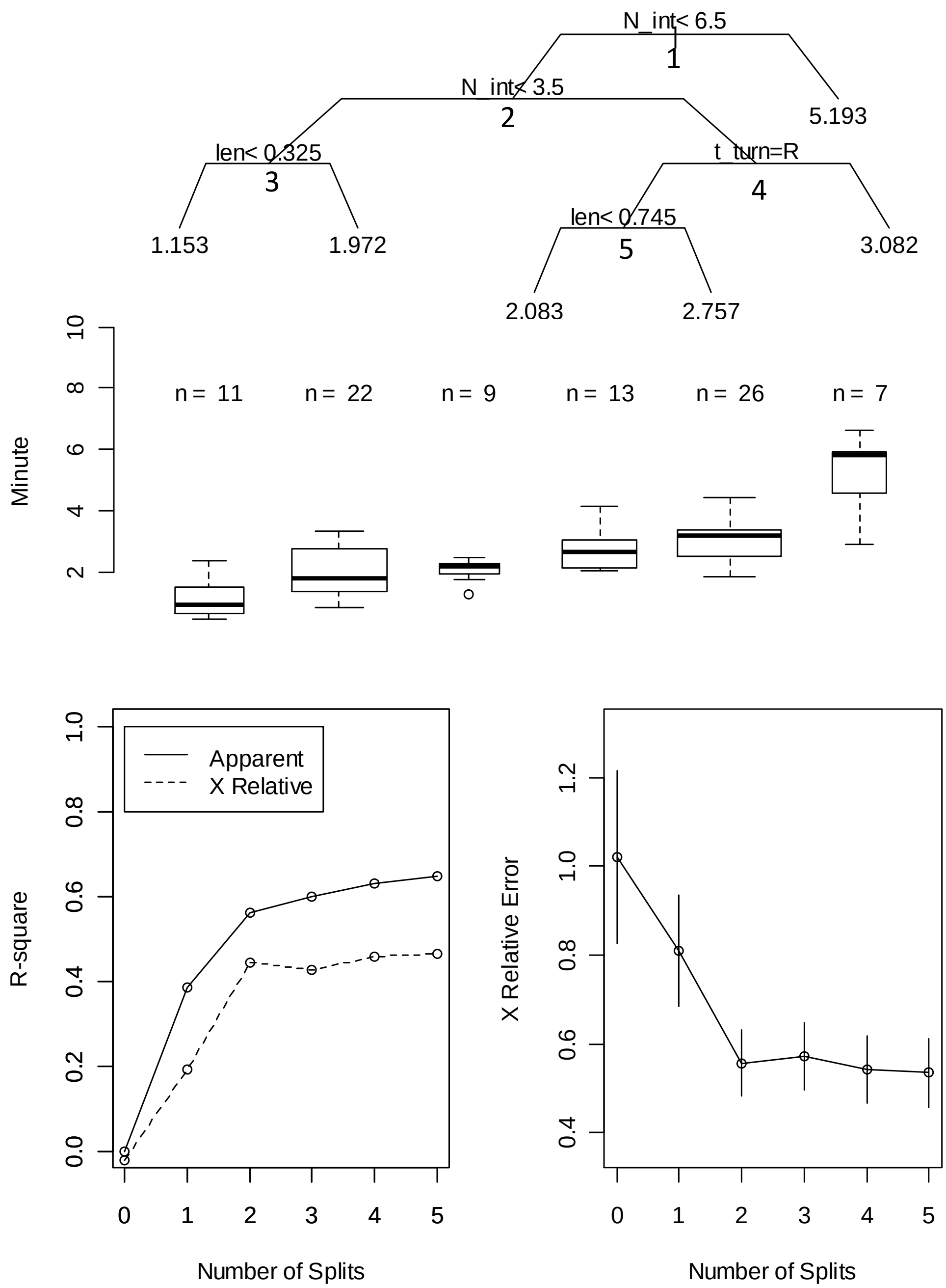


Figure 41: Tree model for AM peak (07:00 to 09:00) group of random route data

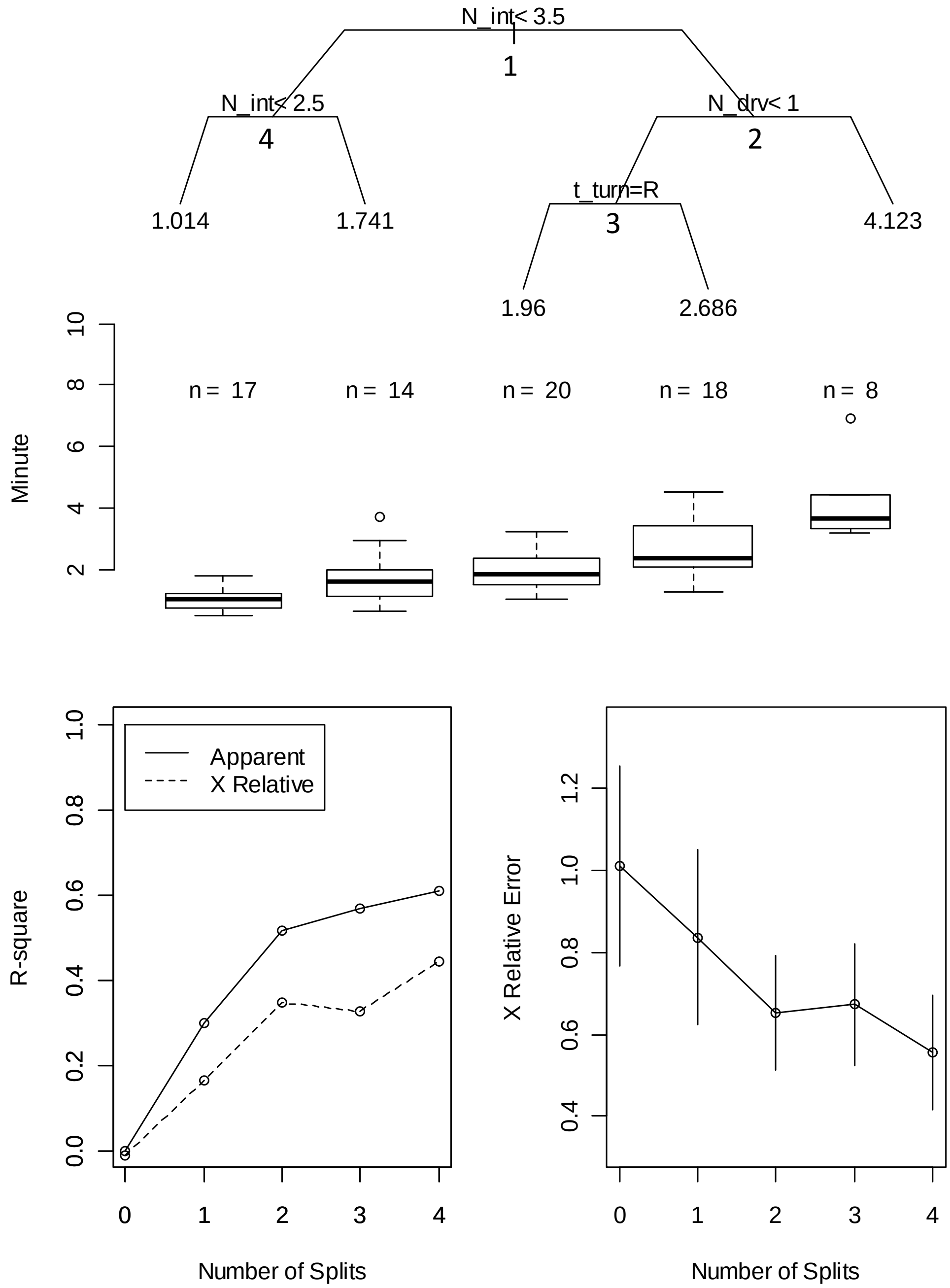


Figure 42: Tree model for 09:00 to 11:00 group of random route data

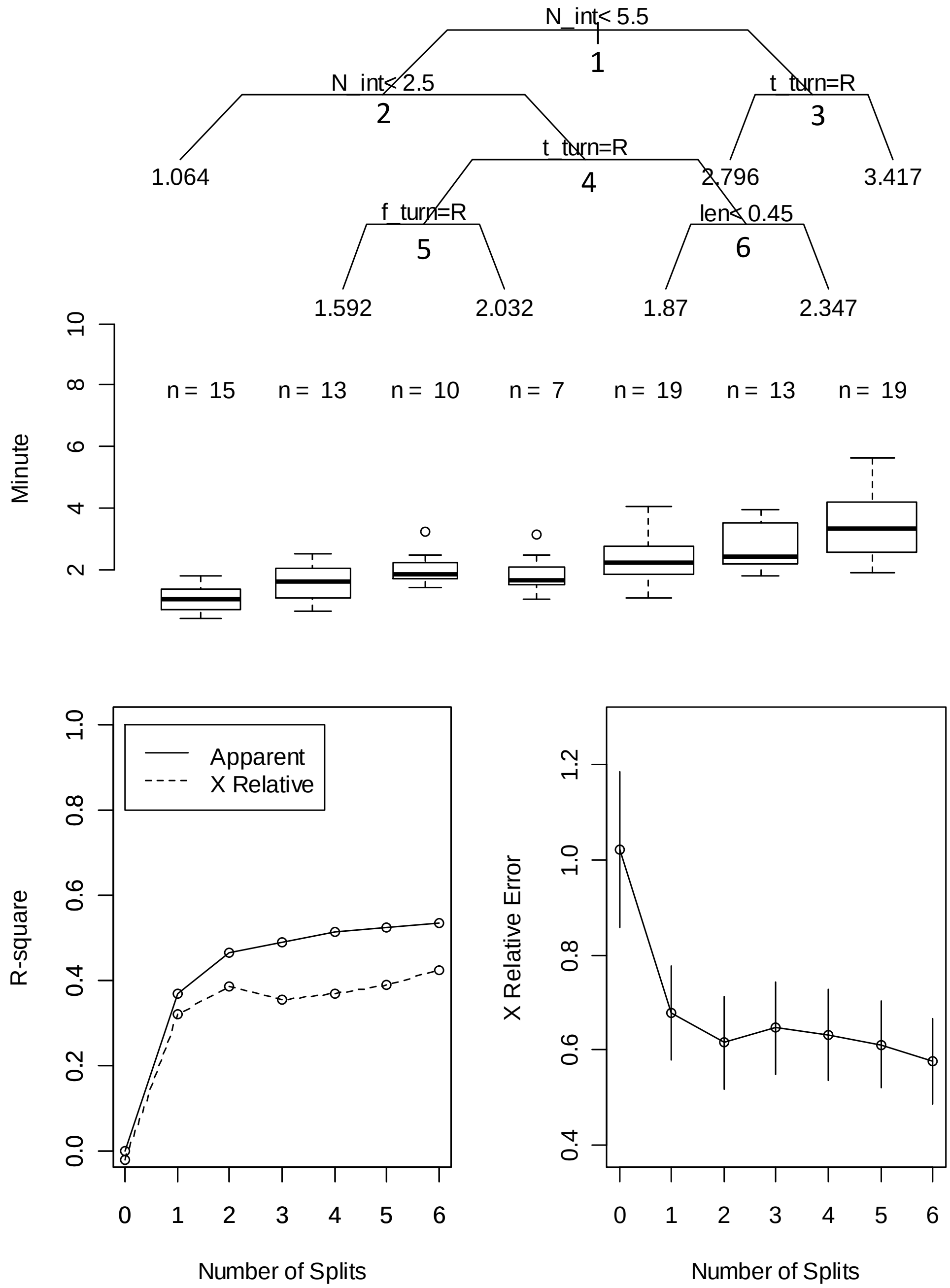


Figure 43: Tree model for 11:00 to 13:00 group of random route data

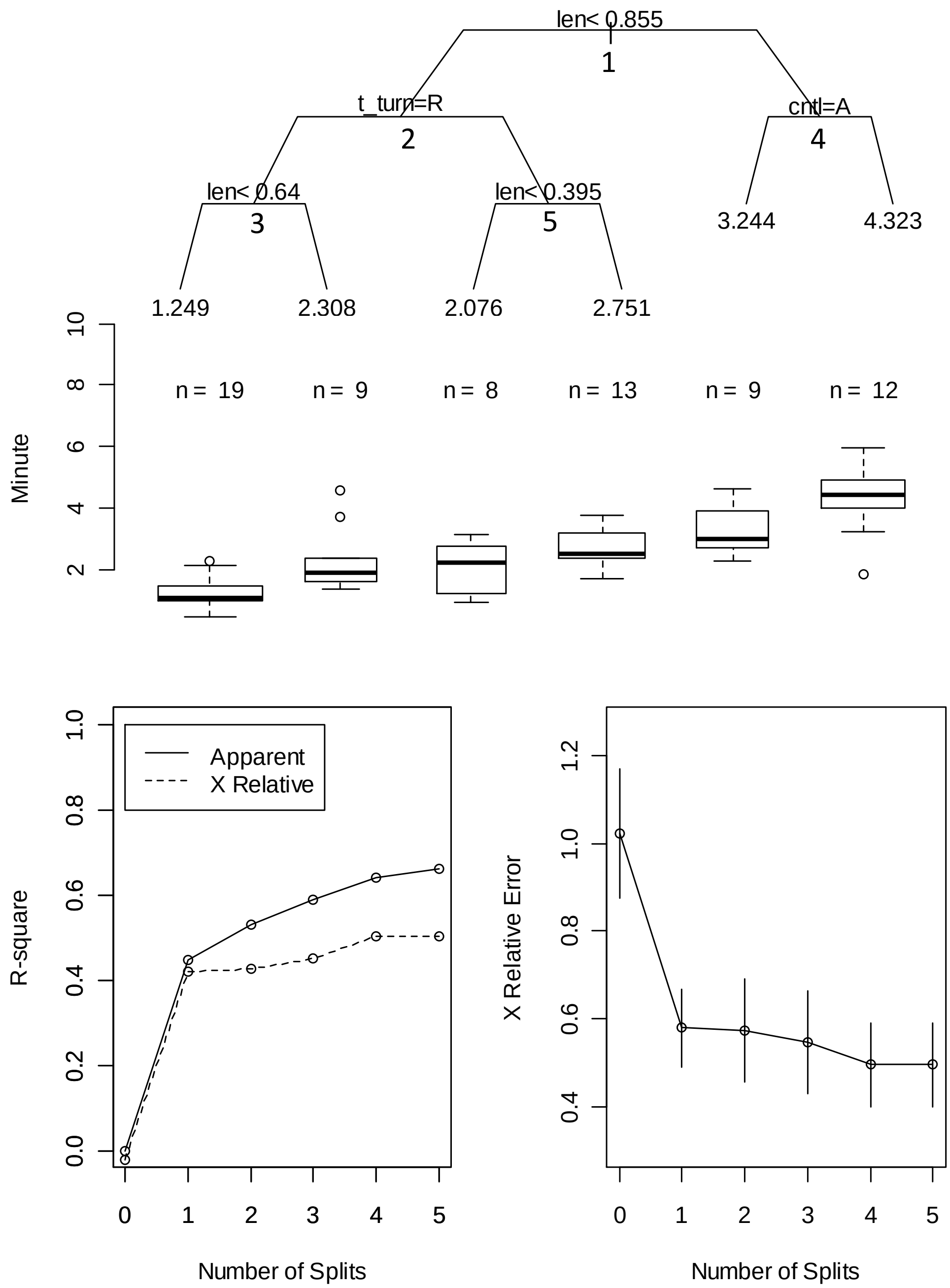


Figure 44: Tree model for PM peak (17:00 to 19:00) group of random route data

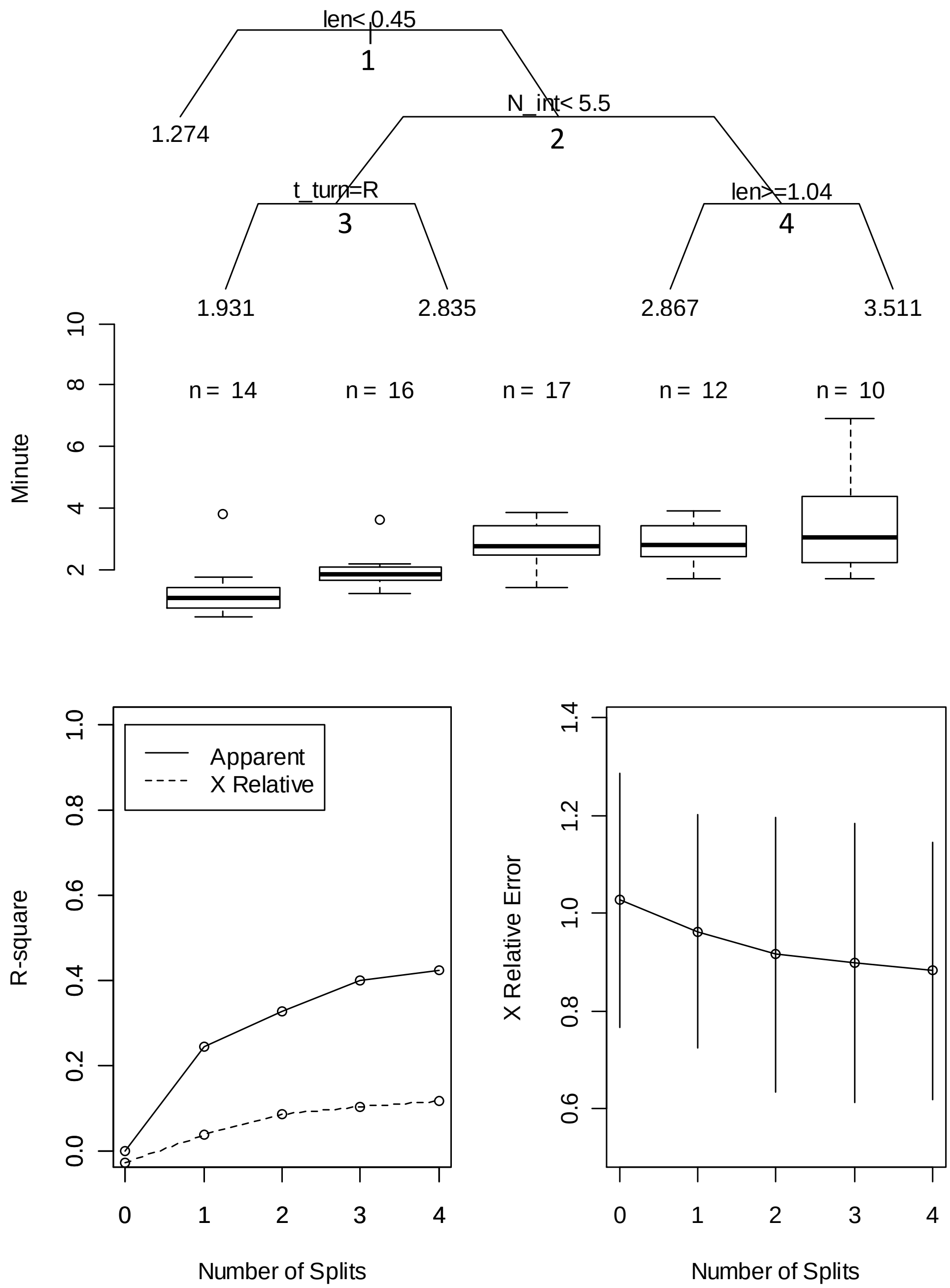


Figure 45: Tree model for Saturday group of random route data

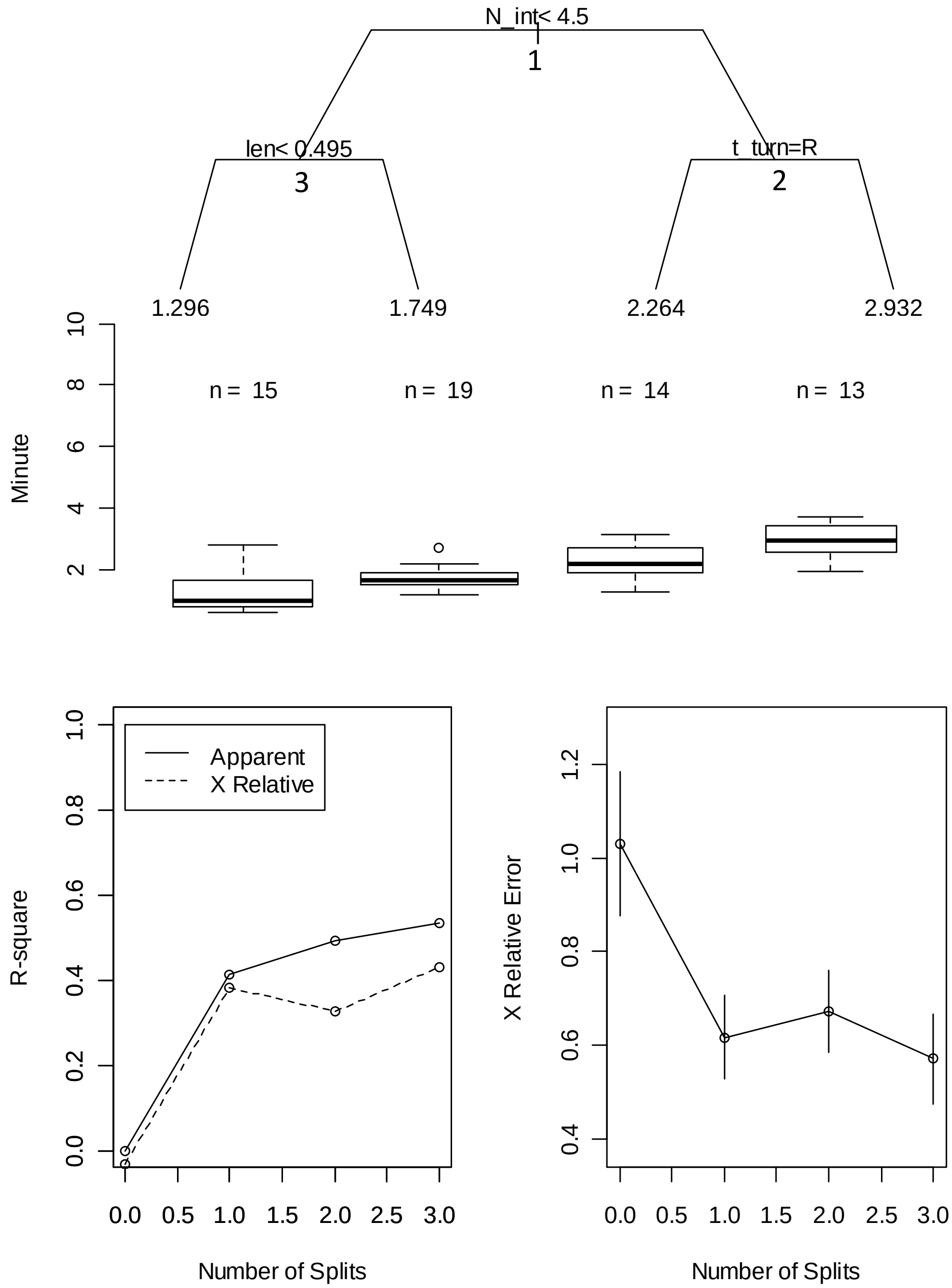


Figure 46: Tree model for Sunday group of random route data

Results of time period models

Figure 41 to Figure 46 show the final trees and their R-square values for the time period groups of 07:00~09:00 to Sunday. The training error of the models is around 0.6 and the prediction error is around 0.4 except for Saturday group. Relatively low accuracy of Saturday tree model may be due to the wide distribution of data in the rightmost final node. The node includes travel runs that passed over five intersections but whose travel length was shorter than 1.04 mile. Considering the geographic layout of the study intersections, these conditions are satisfied only when test vehicle routes encompass all intersections at I-285 on-off ramps and Cumberland Parkway and some intersections on one-lane segments in the east part of Paces Ferry Road. The characteristics of the runs in the node were examined using the travel time database, but a clear explanation could not be found.

For AM peak group, number of intersection passed was the most dominant variable. During 09:00 to 11:00, number of driveways on one-lane segments was the second most important variable following number of intersection passed. For 11:00~13:00 and Sunday group, number of intersection passed and turn type at destination intersection were important variables. For PM peak group, travel length, turn type at destination intersection, and control type were statistically significant variables. For Saturday group, travel length and number of intersection passed were dominant factors.

As discussed, travel length (len), number of intersections passed (N_int), and turning direction at destination intersection (t_turn) were identified as significant split variables in most tree model results. The number of driveways on one-lane segments was selected in the final tree of 09:00~11:00 group, in which if a travel was relatively long, a positive value of this variable caused longer travel time. Turning direction at origin intersection was selected in the result of 11:00~13:00 group, in which if a run is moderately long (three to five intersections passed) and ends by right turn, the left turn at origin intersection is associated with longer travel time. Likely those runs entering Paces Ferry Road from a left turn off a side street did not directly enter a green band. Among all groups, the control system change had a significant effect on travel time in only 17:00~19:00 group. When travel length was relatively long (>0.855 mile) SCATS increased travel time. For comparison with the fixed route data analysis in the previous chapter, Figure 47 displays the rectangle graph of fixed routes for PM peak period. The rectangles were generated based on the confidence interval of mean under ACTRA and SCATS using the proposed bootstrap sampling. Each rectangle represents each fixed route, and if a rectangle is below the line, SCATS significantly decreased the route travel time. The rectangles of route A and B, i.e. the routes that traverse Paces Ferry Road, are below the line in part but cross the line. Except for route D and F, the rectangles of other routes also touch the line. Summarizing these results, control strategies were not statistically significant for end-to-end type runs on Paces Ferry road in PM peak period.

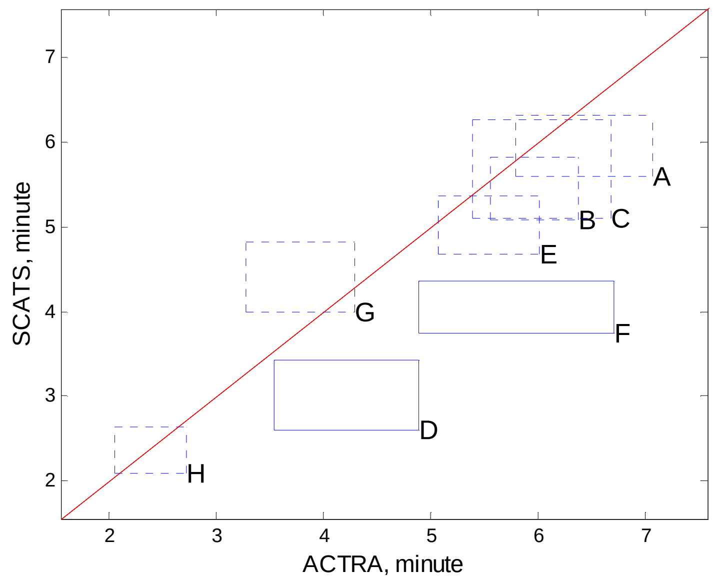


Figure 47: Comparison of confidence interval of mean for all fixed routes in PM peak

Summary

Speeds on random routes and fixed routes were compared and it was found that side street originating travel runs were generally slower under ACTRA. This result is considered reasonable as in semi-actuated coordinated control, the major feature of ACTRA, signal coordination along major corridors tends to provide minimal consideration of coordination of side street originating traffic. This speed difference was not salient under SCATS.

To examine the control system change effect on random routes, binary tree models were developed for the entire data and the time period group data. As independent variables, control system type, time period (for the entire data model) and geometric conditions were used and travel time observations were used as responses. Control type is among split variables in the entire data model, but its contribution to model accuracy improvements is very small. Among all time period groups, the control system change had a statistically significant effect on travel time in only 17:00~19:00 group, in which SCATS increased travel time of relatively long (>0.855 mile) routes. On the other hand, the fixed route data analysis showed that control strategies were not significant on end-to-end type routes in the same period although travel time decreases were observed on a majority of routes.

CHAPTER 7. SYSTEM-WIDE MEASURE, TRIP TIME VERSUS STOP TIME RELATION

In the 1970s General Motors Laboratories investigated speed-time history data of test vehicles collected in nine metropolitan areas in the U.S. to characterize traffic on different types of roadways with different levels of traffic demand *(72)*. Although traffic characteristics in those areas are different, simple and global trends were observed between traffic variables, for example, stop time per unit distance is linearly related to trip time per unit distance. This simple trend was also observed in Berkeley and Fresno, California, Detroit, Michigan, London, England and Melbourne, Australia *(72-74)*. The existence of the linear relationship in the data from different areas motivated the examination on the theoretical basis for such a trend and as a result, the two-fluid model for non-highway urban traffic was suggested *(73)*. Later, the model assumptions (discussed in the next section) were verified in an urban street network *(75)* and at an arterial level *(76)*.

Two-fluid model characterizes traffic of an urban street network system using the relation between stop time and trip time. This relationship is characterized by two parameters: minimum average trip time per unit distance and a parameter relating the change in trip time to that of stop time. The former describes the quality of network service when traffic demand is the lowest and the latter relates to the trend of the trip time change as traffic concentration increases. Using these properties, attempts were made to assess the changes of traffic signal control schemes in urban street network systems and this model was shown to be effective in detecting those changes *(75, 77, 78)*.

Given this background, this study attempts to evaluate SCATS in Cobb County, Georgia using the trip time versus stop time relation. Under the two-fluid model framework, this relationship can help to determine the fraction of moving or stopped vehicles in the network that can be used as a system-wide performance measure of the control system. This quantity is referred to as a system-wide measure because it aggregates traffic conditions of different routes and time periods and higher weights are given to the higher demand traffic conditions (further details are discussed later). In this context the "system" is defined to be the area in which the control strategy has been implemented. It is not intended to imply that this measure necessarily incorporates potential impacts to the full "transportation system". That is, it is possible that the control strategy impacts performance (due to travel pattern changes) outside of the implementation area that are not captured in this measure.

In early 2005 Cobb County Georgia replaced the existing semi-actuated coordinated signal control, referred to as ACTRA, with SCATS at fifteen intersections on Atlanta Road, Paces Ferry Road and Cumberland Parkway in an attempt to improve traffic flow, reduce congestion, and reduce signal re-timing costs *(38)*. This research uses data previously collected by the Cobb County SCATS evaluation study that was designed to evaluate the performance of the new control strategy. This study used a series of instrumented test vehicles to record travel times on various routes through this network. To cover the study area in a complete fashion, two types of test vehicle routes were devised: fixed routes to determine end-to-end travel times and a series of random routes used to determine side-street to side-street travel times. The two-fluid model approach is applied to the data from the two different types of routes to evaluate the impact of the new control system on different travel patterns. The rationale for using this approach is that while traditional traffic signal evaluation approaches evaluate different routes and time periods in a disaggregated sense *(36-41, 43, 45),* the two-fluid model evaluates the impact of these signal controls by aggregating data across various time periods and routes thereby allowing a system-wide signal control effect on the study area to be examined.

Two-Fluid Model

Model development

Under this model, traffic in an urban street network is considered to comprise two fluids: one of moving cars and the other of stopped cars as a result of congestion, traffic signals, stop signs, and other factors *(73)*. It is assumed that the average space mean speed of moving vehicles, v_r, is dependent on the fraction of moving vehicles in the network, namely,

$$v_r = v_m f_r^n = v_m(1 - f_s)^n \quad (1)$$

where, v_m is the average maximum running speed; f_r and f_s are the fraction of moving and stopped vehicles in the network respectively; and n is fitted parameter relating the change in trip time to changes in stop time. Note that $v_m = 1/T_m$, where T_m is the average minimum trip time per unit distance. The model further assumes that the average fraction of the stopped time for a vehicle (stop time per unit distance over trip time per unit distance, $\frac{T_s}{T}$) is equal to the fraction of stopped vehicles in the network over the same time period, during which traffic concentration or traffic demand is stable over time and space *(73)*. This assumption can be written as:

$$f_s = \frac{T_s}{T}. \tag{2}$$

From Equation 1 we therefore have,

$$v_r = T_m^{-1}(1 - f_s)^n. \tag{3}$$

Since $v = v_r f_r$, then

$$v = T^{-1} = T_m^{-1}(1 - f_s)^n f_r = T_m^{-1}(1 - f_s)^{n+1}. \tag{4}$$

Equation 2 and Equation 4 lead to

$$1 - \frac{T_s}{T} = \left(\frac{T_m}{T}\right)^{\frac{1}{n+1}}. \tag{5}$$

Solving Equation 5 for T_s, the following result is obtained.

$$T_s = T - T_m^{\frac{1}{n+1}} T^{\frac{n}{n+1}} \tag{6}$$

It should be noted that all variables in the two-fluid model are meant to be averages over the entire system. Since trip time is the sum of running time and stop time, that is, $T = T_r + T_s$, equation 6 can be rewritten as

$$T_r = T_m^{\frac{1}{n+1}} T^{\frac{n}{n+1}}. \tag{7}$$

(The preceding nomenclature and Equations (1) through (7) are taken from *(73)*)

Model interpretation

Two-fluid model parameters, T_m and n, can represent the quality of traffic service of an urban street network. The slope dT/dT_s can be expressed as a function of T_m and n *(79)*, given by

$$\frac{dT}{dT_s} = \left\{1 - \left[\frac{n}{n+1}\right]\left(\frac{T_m}{T}\right)^{\frac{1}{n+1}}\right\}^{-1}. \tag{8}$$

Typical ranges of the two parameters, T_m and n are from 1.5 min/mile (40 mph) to 3.0 min/mile (20 mph) and from 0.8 to 3.0, respectively *(77)*. Figure 48 illustrates T versus T_s curves with T_m = 2 min/mile and 3 min/mile; and n =1, 2, and 3. The curvature of the curves is small and a linear trend between the two variables is a good approximation that was observed in many metropolitan areas. Based on Equation 8 and the illustrative curves in Figure 48, it can be seen that a higher value of n relates to a steeper slope. A curve with a steeper slope produces a greater change in trip time per unit distance for a given change in stop time per unit distance *(75)*. Thus, most two-fluid model literature interpreted the parameter n in such a way that the network with a lower value of n is more resilient in terms of maintaining the quality of service to increases of traffic concentration or travel demand*(73)*. On the other hand, the minimum trip time per unit distance, T_m, represents the service quality when the demand is the lowest and the trip time is governed by only traffic control devices, meaning that a higher value of T_m generally implies poor signal timing or poor road geometry *(80)*.

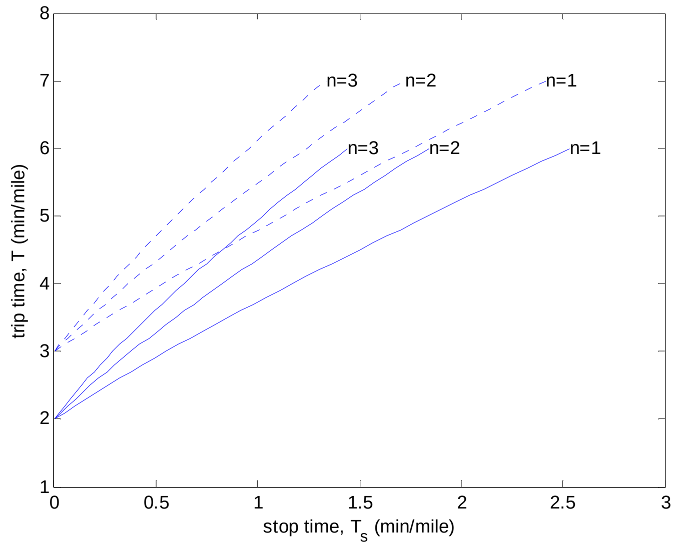


Figure 48: Trip time versus trip time for T_m =2 min/mile and 3 min/mile; and n =1, 2, and 3

Based on this interpretation, it can be said that an urban signalized street network with smaller T_m and n generally performs better over the range of traffic concentrations. This interpretation assumes that the traffic concentration level is represented by stop time per unit distance, T_s, and thus trip time per unit distance, T, is interpreted as a dependent variable. However if T is taken as the independent variable to represent the congestion level, a higher value of n means that the stop time increases less rapidly than the congestion level. This interpretation has been provided by Williams, Mahmassani, and Herman in a study to evaluate the signal coordination effect, the result of which indicated that the coordinated system reduced stop time at the same level as trip time *(78)*. This research acknowledges this conflict in model interpretations and presents an alternative interpretation in which a focus lies in realistic ranges of T and T_s instead of the model parameters.

Application

As the two-fluid model provides a simple relationship between trip time and stop time, and thus does not depend on traffic characteristics of a specific area, a common application has been the comparison of the network service quality among different cities *(72, 75, 79, 80)*. Other applications include the study on network-level traffic flow relations *(81)*, extreme driver behaviors *(82)*, and the calibration of a microscopic simulation model *(77)*.

Methodology

General procedure

The fixed and the random route data were initially grouped by period-route-control combinations in preparation for further processing. After that, the key input data to estimate the parameters of the two-fluid model, trip time per unit distance and stop time per unit distance (T and T_s), were evaluated for each group by aggregating the individual trip (travel) times and stop times. This aggregation was achieved by summing the trip times and stop times of individual test vehicles in a group and then dividing them by the total traveled distance. The resulting values of T and T_s of the groups under ACTRA and SCATS were then compared for each period-route level and the two fluid model parameters were estimated. The resulting trend curves generated by the parameters were then compared and interpreted.

Stop time definition

The two-fluid model was developed by analogy to Bose-Einstein condensation theory describing the behavior of integer spin molecules in their ground and excited states *(73)*. In the transportation application, the stop time is considered to be analogous to time when a molecule is in the ground state and is thus counted while the speed of test vehicles was zero. The adopted GPS equipment in the test vehicles recorded the speed at one second intervals, so the stop time is the sum of the seconds with zero speed.

Chase vehicle versus test vehicle

The chase vehicle method, in which a data collection vehicle follows a randomly selected vehicle to collect travel times on representative routes of the network in a random fashion, has often been used in previous studies in the two-fluid model literature. Since this study uses test vehicle data collected for the Cobb County SCATS evaluation study, some portions of the network may have been sampled more than their actual usage. To limit the impact of this issue, the data were aggregated by defined routes (presented later) that were believed to be representative of the study area.

Reasons for group data aggregation

Applications of the two-fluid model often used individual travel time data to estimate the parameters. However, since the variables in the two fluid model are system averages, aggregating individual travel times in a time period is more appropriate. It was found that model parameter estimation is more consistent when aggregated data are used *(83)*. Also, as the sample size of groups of different routes, time periods, and control systems are different, the aggregation helps obtain balanced model input data.

ACTRA and SCATS comparison at the disaggregate group level

After T and T_s are evaluated in all the groups of period-route-control combinations, the values of T and T_s of SCATS are compared with those of ACTRA at each group. This comparison results at disaggregate levels are later used to verify the interpretation of estimated model parameters defining the general trend between T and T_s.

Parameter estimation

Applying the log function to both sides of Equation 7 transforms a curvilinear relation between T and T_s into a linear relation *(75)*. Then, the parameters can be estimated from the values of T and T_s of the groups using the least squares method in conjunction with a simple linear regression model. The log transformation of Equation 7 follows that

$$logT_r = \frac{1}{n+1} logT_m + \frac{n}{n+1} logT \qquad (9)$$

$$or\ logT_r = A + BlogT, \qquad (10)$$

$$with\ n = \frac{B}{1-B}\ and\ logT_m = \frac{A}{1-B}. \qquad (11)$$

(The preceding nomenclature and Equations (9) through (11) are taken from *(75)*)

Data

Sample size by period-route-control group

The travel time data under each control method need to be aggregated for the reasons discussed earlier. The fixed route data are grouped by six time periods (four two-hour periods for weekdays and two four-hour periods of for weekend days) and eight routes (A to H), resulting in forty-eight groups under each control method. The sample size of a fixed route group ranges from 8 to 31 runs. For the random route, the turning direction (right turn or left turn) at the ending intersection is used to define routes and the data are grouped by six time periods and the two turning directions, resulting in twelve groups for each control method. For the original purpose of the random route data collection, capturing the possible disadvantage of a control method toward minor street traffic, all test vehicle runs originating from major roads (i.e. Atlanta Road and Cumberland parkway and I-285 exit ramps) were excluded. The sample size of a random route group ranges from 10 to 38 runs. The sample size of the period-route-control groups of the fixed routes is previously presented in Table 9 of Chapter 4 while that of the random data is shown in Table 16.

Table 16: Sample size of random route data for two-fluid model (unit: run)

Time period	Route		Grand Total
	Right turn at end	Left turn at end	
ACTRA total	**86**	**103**	**189**
7:00~9:00	19	22	41
9:00~11:00	13	11	24
11:00~13:00	15	13	28
17:00~19:00	10	13	23
Saturday	15	24	39
Sunday	14	20	34
SCATS total	**129**	**143**	**272**
7:00~9:00	22	25	47
9:00~11:00	29	24	53
11:00~13:00	30	38	68
17:00~19:00	23	24	47
Saturday	13	17	30
Sunday	12	15	27
Grand total	**215**	**246**	**461**

Results

ACTRA and SCATS comparison at disaggregate group level

For the forty-eight period-route groups of the fixed route data, trip time per unit distance, T and stop time per unit distance, T_s under ACTRA and SCATS were compared. Note that the term "increased" or "decreased" in Table 17 means that the value of a variable increased or decreased under SCATS. In thirty-two groups (about 70% of all), SCATS decreased T and T_s. Figure 49 (a) and (b) graphically shows the changes of T and T_s respectively. The x-y coordinate of each point is the value pair of a variable under ACTRA and SCATS of the same period-route group. In the figure, the line with the slope = 1 visually helps to see the amount of the change. For both trip time and stop time data, the amount of the increase or decrease was small in a lower range, but the amount of the decrease was relatively large in the higher ranges. These results imply that SCATS performed relatively well when traffic concentration is higher for the end-to-end travel time runs.

Trip time per unit distance, T and stop time per unit distance, T_s under ACTRA and SCATS were compared for the twelve period-route groups of the random route data. The results are also summarized in Table 17 and Figure 49 (c) and (d). T increased in 50% of the groups. A noticeable difference from the results of the fixed route data is that T_s increased in a majority of the groups under SCATS. For both T and T_s the amount of the increase was relatively large. Summarizing these results, ACTRA performed relatively well in terms of stop time for the side street-to-side street travel time runs.

Figure 49 also illustrates that the ranges of T and T_s are generally higher for the random routes runs. A major reason can be that the test vehicle cleared the last intersection by turning movements, which involves more delays than that of passing through that is incorporated for the fixed route runs. Another reason may be the disadvantage of the random routes from the signal coordination for major corridor traffic.

Table 17: Number of groups by change of T and T_s under SCATS

	Fixed route		Random route	
	T	T_s	T	T_s
Total # of group	48	48	12	12
# group with increased	15	15	6	9
# group with decreased	33	33	6	3
# group with increased T, increased T_s	14		6	
# group with decreased T, decreased T_s	32		3	
# group with increased T, decreased T_s	1		0	
# group with decreased T, increased T_s	1		3	

Note: “increased” or “decreased” means that the value of a variable increased or decreased under SCATS

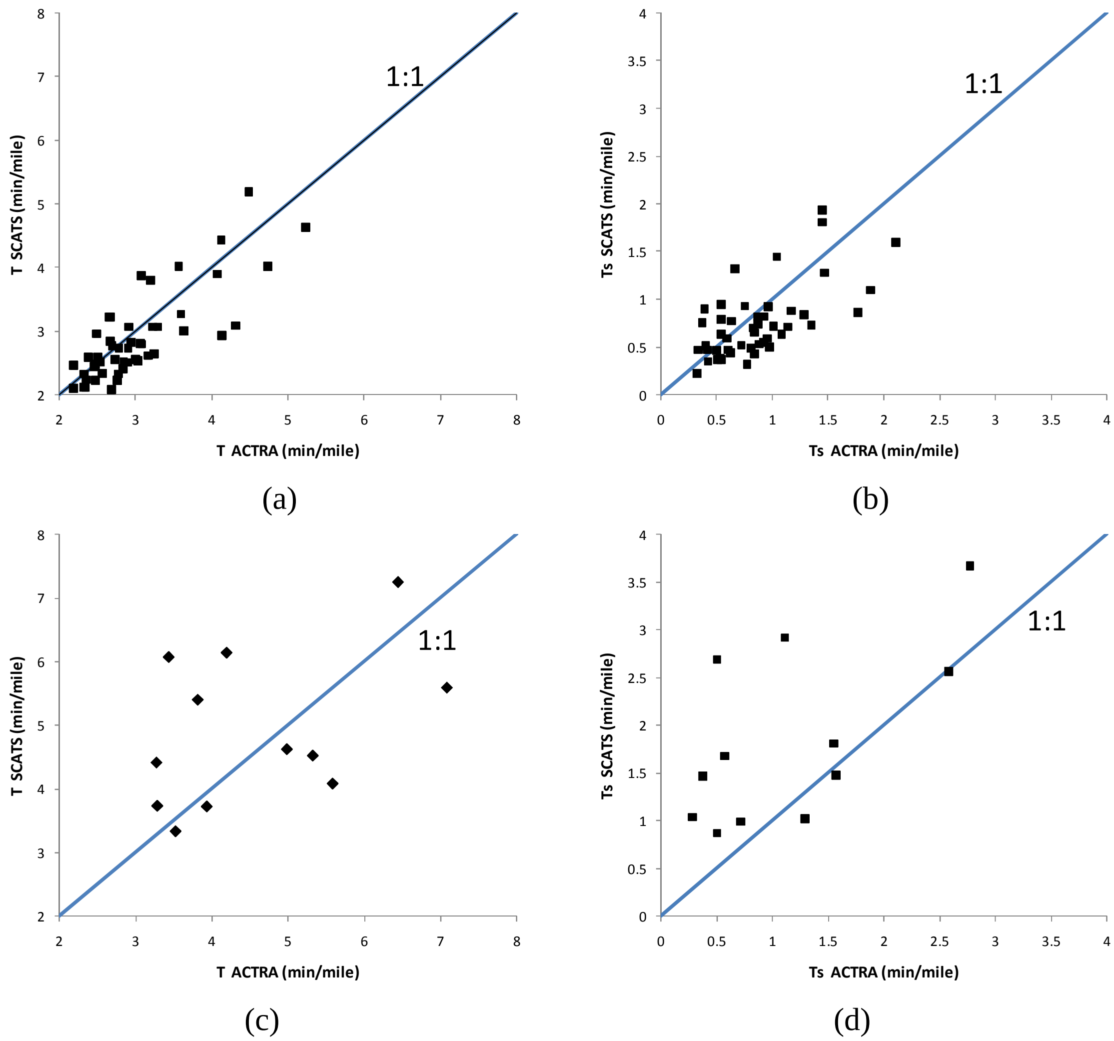


Figure 49: ACTRA and SCATS comparison at disaggregate group level (a) T ACTRA versus T SCATS, fixed route data (b) T_s ACTRA versus T_s SCATS, fixed route data (c) T ACTRA versus T SCATS, random route data (d) T_s ACTRA versus T_s SCATS, random route data

Interpretation of trip time vs. stop time relation based on two-fluid model parameter values

The two-fluid model parameters were estimated based on the values of T and T_s representing the fixed route and the random route groups using a log-transformation. Figure 50 shows the parameter values and the trend curves generated by Equation 6. The curves fit the data well over a wide range of T and T_s. The R^2 value of the fits ranges from 0.73 to 0.92 in the transformed scale.

For the fixed route data, the average minimum trip time per unit distance, T_m decreased from 1.31 min/mile to 1.11 min/mile while the slope parameter, n increased from 1.58 to 2.31. Following the general interpretation of the two-fluid model discussed earlier, SCATS performed better when traffic concentration was the lowest but as the traffic concentration increased (T_s increases), the trip time of SCATS increased faster. This higher rate increase is observed after the trend curves of ACTRA and SCATS intersect with each other at around the point of (0.5 min/mile, 2.3 min/mile) and a majority of the data points belong to this region. For the random route data, the average minimum trip time per unit distance, T_m decreased from 2.59 min/mile to 2.14 min/mile and the slope parameter, n also decreased from 1.00 to 0.77. Based on these values, SCATS performed better when traffic demand was the lowest and the trip time increasing rate is lower as the traffic concentration level increased.

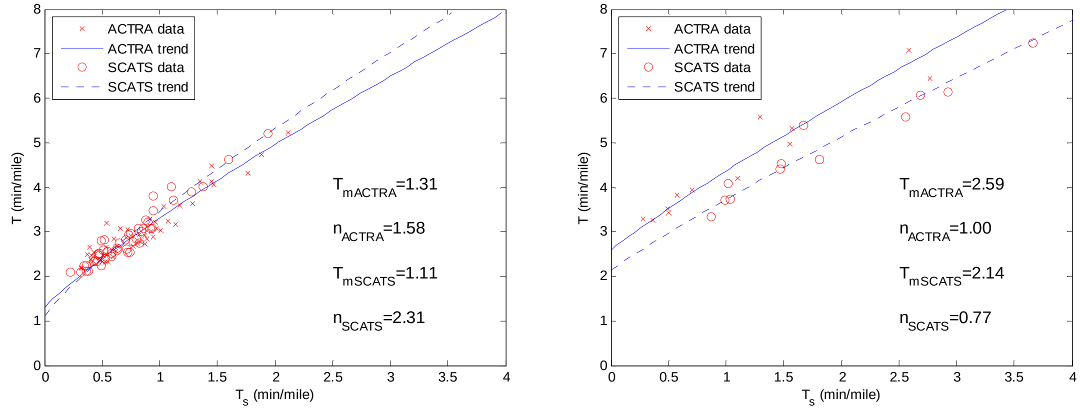


Figure 50: Trip time vs. stop time based on fixed route data (left), random route data (right)

As seen, the results above show different superiorities from the disaggregate group level comparison, in which SCATS was better in more groups of the end-to-end runs and ACTRA was better in terms of stop time for the side street-to-side street runs. Another noticeable issue is that the estimated values of average minimum trip time per unit distance, T_m for the fixed route data are too low, below the lower bound of the typical range cited earlier, 1.5 min/mile. Specifically, the average maximum speed of 54 mph (reciprocal of 1.11 min/mile) under SCATS is not realistic in the study area with a speed limit of 35 mph on most roadway segments and high intersection density of 3 to 6 intersections per mile even if the traffic demand is the lowest.

The above issues may be due to the nature of the two analysis approaches. In the disaggregate level analysis, each group is equally weighted, but in the two-fluid model approach, higher valued groups representing heavier traffic conditions are more highly weighted to determine the parameters. While the former approach examines only the observed data range, the latter approach is able to predict the system performance under extreme conditions, for example higher-than-observed or zero stop time. It is likely that these conditions are rarely observed, and less interesting in a control system evaluation study. However, the benefit of the system-wide aggregation (even over different time periods) is what the disaggregate level analysis is lacking in. Therefore, this research presents a modified version of the two-fluid model interpretation, considering realistic ranges for T and T_s.

Interpretation of trip time vs. stop time relation considering variable range

The general interpretation of the two-fluid model parameters implicitly assumed that the minimum value of T_s is zero. However as seen in Figure 50, the observed minimum values of T_s are bounded at some values before reaching zero, and thus T_m may not be a practical minimum of T. T_s being greater than zero is more realistic because the average minimum stop time is likely greater than zero in an urban signalized network environment. Another implicit assumption is that the range of T_s is identical for compared systems, which is possible only when the boundary values and the marginal increases are identical. This assumption also is not well satisfied as seen in Figure 50 (right), in which the ranges of T_s are different for ACTRA and SCATS. In this context, the interpretation depending mainly on T_m and n may not be practical.

To address the discussed issues, a new interpretation that combines the disaggregate group analysis and the two fluid model approach by taking advantages of them is presented. On a plane generated by two variables, T_s and T, the location of a point defined by a specific value pair of (T_s, T), which represents a specific period-route group, moves to another location by a change of control strategy. Aggregating these point-wise movements, the trend curve representing trip time versus stop time relation of the network changes its location and shape on the plane. The curve is bounded by the minimum and the maximum value of T and T_s that may be determined by the conditions of speed limit, geometry, demand, and control. In this research, the movement of the curves was caused only by the change of control system because the other conditions remained unchanged, which is a typical assumption in a before-and-after type study. To apply this modified approach, the ranges of the trend curves in Figure 50 need to be defined. Figure 51 shows the resulting curves generated for the fixed and the random route data with the maximum and the minimum values defined by the observed ranges of T in Figure 50. Using the ranges of T_s results in similar curves but as the arterial service quality is determined by average space mean speed (reciprocal of T), using the ranges of observed T may be more appropriate.

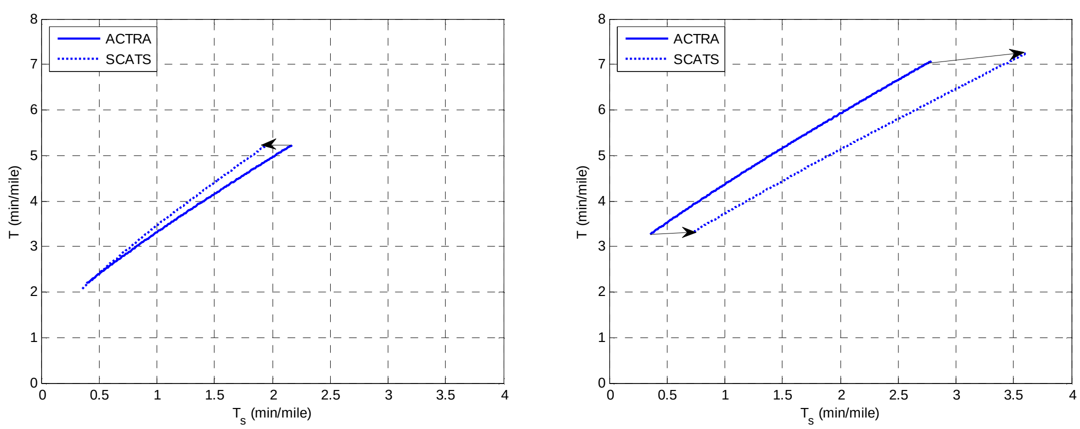


Figure 51: Range-restricted curve of trip time vs. stop time relation based on fixed route data (left), random route data (right)

Based on this approach, T_s is not a reference variable to assess T over a range of traffic concentration because the range of T_s is not fixed for the compared systems. For the fixed route data, the trend curve rotates counterclockwise with the rotation center almost fixed at around (0.3 min/mile, 2 min/mile) and the maximum of T bounded at around 5.2 min/mile (Figure 51 (left)). Given the movement of the curve, SCATS did not make a noticeable difference in a lower range of T, for example up to 3 min/mile (reciprocal of 20 mph), but in the higher range, SCATS less increased T_s as T increased. When the network is most congested, with an average speed of around 11 mph, a vehicle would experience less stop time by about 0.24 minute/mile on average under SCATS control. For the random route data, SCATS moved the curve to the right, while the length slightly increased and the range of T was almost unchanged. Because the two curves do not intersect with each other, at any level of traffic concentration T_s increased under SCATS. As the SCATS curve is longer and less steep, the amount of the increase of T_s becomes larger in a higher range of traffic concentration. It is about 0.38 min/mile when traffic concentration is the lowest and about 0.82 min/mile in the opposite condition.

When the network was congested, SCATS reduced stop time for the end-to-end travel runs. However, SCATS increased stop time for the side street originating travel runs at any level of congestion. Caution should be taken in combining the results from these different travel pattern data sets. Although the size of the increase of stop time on an unit length of the side street-to-side street type routes is larger than that of the decrease of stop time on an unit length of the end-to-end type routes, it is difficult to tell that SCATS performed worse in terms of the network-wide performance because the actual vehicle-miles on major arterials, represented by the end-to-end runs, is likely to be much higher especially when the network is in peak conditions.

Fraction of moving vehicles (f_r) in network

The average fraction of moving vehicles in a given network can be a system-wide service quality measure. From Equation 2 and the second assumption of the two-fluid model, the average fraction of moving vehicles in the network can be written as

$$f_r = (T - T_s)/T. \qquad (12)$$

Using this equation, the fraction can be calculated at a point on the curves in Figure 51. If it is assumed that a point on ACTRA matches with a point on SCTAS curves in an increasing order from the lower to the upper bound, the relation of f_r between ACTRA and SCATS can be obtained. The trend lines representing this relationship are displayed in Figure 52. For the end-to-end traffic, the fraction of moving vehicles under SCATS is not much different from that under ACTRA when traffic demand is the lowest (at the upper bound of the line in Figure 52 (left)). However, as traffic demand increases, the marginal decrease of the fraction is smaller under SCATS. When the demand is the highest (at the lower bound of the line in Figure 52 (left)), about 10 % more vehicles were moving under SCATS. For the side street originating traffic, the fraction of moving vehicles under SCATS is lower in any traffic concentration level. When the network is least congested (at the upper bound of the line in Figure 52 (right)), about 15% less vehicles were moving under SCATS. When the network is most congested (at the lower bound of the line in Figure 52 (right)), about 20 % less vehicles were moving.

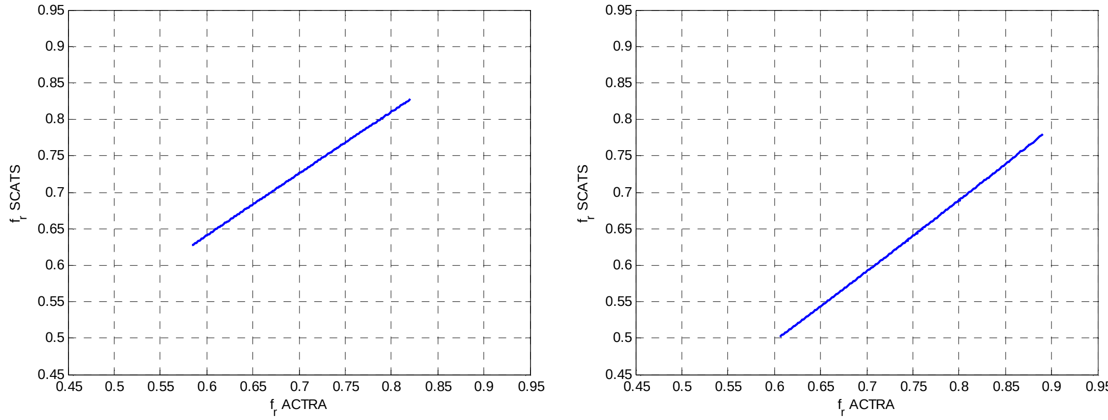


Figure 52: f_r ACTRA vs. f_r SCATS based on fixed route data (left), random route data (right)

Summary

This study compared two traffic control systems using trip time and stop time relation under the two-fluid model theory. The model was developed to find the theoretical basis for the linear trend between trip time and stop time that was observed in urban street networks. The two model parameters are minimum average trip time per unit distance that represents the service quality when the network is least congested and a parameter determining the increasing rate of trip time to stop time. Based on the general interpretation, smaller values of the parameters indicate that the network system performs better when traffic concentration is the lowest and that trip time increases less as stop time increases.

Using the test vehicle data collected for the evaluation of SCATS in Cobb County, Georgia, the parameters were estimated and interpreted. The test vehicle routes were devised in two ways: fixed routes of typical end-to-end runs and random routes of side street-to-side street runs that aim to capture the performance of side street originating traffic. At the initial interpretation, discrepancy of superiority was found between the disaggregate group level comparisons and the model interpretation based only on estimated parameters. At the disaggregate level, SCATS decreased trip time and stop time in more groups based on the fixed route data and ACTRA performed better in more groups in terms of stop time based on the random route data. However, based on the estimated two-fluid model parameters, although SCATS slightly decreased trip time when traffic concentration is the lowest, it increased trip time faster in the overall range of stop time for the fixed routes and SCATS decreased trip time in any level of stop time for the random routes. This discrepancy may be due to the nature of the two approaches. The disaggregate approach equally weights individual groups, but the two-fluid approach places more weights on the higher valued groups by solving for a regression line. The latter is able to predict the system performance under extreme conditions that may be rarely observed.

A new interpretation that combines the two different approaches was presented. Under this approach, the curve defining trip time versus stop time relation is bounded by traffic conditions and it moves and changes its shape by the control change. The new interpretation resulted that SCATS did not change trip time but that reduced stop time when the network is congested for the fixed routes. Also the interpretation indicates that SCATS increased stop time in any traffic concentration level for the random routes.

Based on the curves defining trip time versus stop time relation, the fraction of moving vehicles in the network can be obtained using the model assumption. As this measure (actually curve) is defined by all time periods and routes data, and heavier traffic conditions are weighted more in the two-fluid model, it can be used as a system-wide performance indicator. Based on this measure, under SCTAS about 10% more vehicles were moving on the fixed routes when the network was congested and 15% to 20% less vehicles were moving on the random routes depending on traffic concentration levels.

It should be noted that the new approach restricting variable ranges may be effective only for a before-and-after type study, in which except the experimental factor, all other conditions are assumed to be unchanged and thus the boundary values are determined by the factor. In comparing the service quality of different cities, which was a common application of the two-fluid model, this assumption may not hold.

CHAPTER 8. CONCLUSIONS

Summary

With growing congestion problems in urban streets, adaptive traffic control has been implemented on arterials in many metropolitan areas. To quantify the new control effect, relevant measures and spatial scope should be selected. Most existing adaptive traffic control evaluation studies investigate average travel time or delay on major street end-to-end through movements and average approach delay at selected intersections. However, metrics based only on the central tendency of the system performance may fail to capture the variability experienced by the individual drivers or the impact on trips that are not end-to-end. With this motivation, this research evaluated the performance of an adaptive traffic control system (SCATS) using arterial travel time characteristics that have not previously been fully utilized to study arterial traffic: travel time distribution, travel time reliability, side street traffic performance on a major signalized corridor, and a system-wide performance measure addressing the relationship between trip time and stop time. The analyses were based on comparisons between SCATS and the former system, ACTRA. This section summarizes the findings.

In early 2005 the Cobb County DOT implemented SCATS on fifteen intersections along Paces Ferry Road, Cumberland Parkway, and Atlanta Road, which had been controlled by a semi-actuated coordinated control, ACTRA. The travel time data were collected from November 9, 2004 to December 8, 2004 for ACTRA and from April 12, 2005 to May 15, 2005 for SCATS, using GPS-equipped test vehicles. Along with conventional end-to-end test vehicle routes (fixed routes), random routes were devised to capture the possible delay incurred to side street originating traffic as it traveled on the corridor. After the field travel time study, an initial error checking procedure identified error points that resulted from either drivers or the adopted GPS equipment. Following the initial error checking procedure the data was passed to the developed TRIPTI algorithm. TRIPTI automatically identifies the time a vehicle passes through an intersection on a travel time run. The output of the algorithm is saved into databases for subsequent calculation and analysis of relevant statistics required over different study area sections and time periods.

In the first analysis chapter, the travel time distribution changes on major corridors were examined based on the fixed route data. Firstly, the field travel time distribution of each period-route-control group was compared with three theoretical distributions: normal, log-normal, and gamma. Based on K-S tests, no strong evidence that they are different from the theoretical distributions was found. Next, the shape of distribution under SCATS and ACTRA was compared at each period-route group using three distribution shape statistics: standard deviation, skewness, and kurtosis. The results suggested that more extreme values of those statistics were observed in the ACTRA groups. Next it was found that for ACTRA groups with extreme shape statistic values, the corresponding SCATS groups contained fewer outlier(s), with lower kurtosis values and skewness values was closer to zero. The shape of the distributions of the groups with mid-range skewness and low kurtosis values under ACTRA was also compared with that of corresponding SCATS groups. It was found that SCATS tended to increase the kurtosis of these groups. Thus, classification tree models were built with the improvement of mean and standard deviation as dependent variables and skewness and kurtosis values as independent variables. The model results suggested that the combined ranges of skewness and kurtosis values for the improved class were not identical for the chosen measures.

The next chapter proposed a procedure to statistically test arterial control performance based on reliability measures. Mean, planning time, standard deviation, and buffer time were selected. Through various scatter plots, it was found that standard deviation and buffer time are highly correlated. A non-parametric test, i.e. bootstrap sampling, was utilized to determine if there existed a statically significance difference between the performance under the two control strategies for period route groups. The test results showed that planning time significantly changed in nine groups, mean in six groups, standard deviation in two groups. Buffer time did not change significantly in any group. Regarding the sensitivity of the statistical test of the measures, the test of planning time is generally more sensitive than that of others to a change in the travel time distribution. Finally, it was observed that a significant change in the travel time mean between the control strategies does not always imply a significant change in the reliability measures and vice versa. When multiple measures of a group showed statistically significant changes, the direction of the changes was consistent. Based on statistically significant groups, SCATS performed generally worse on Route A, but better on other routes. In terms of the time period, SCATS performed generally better in the PM peak period. Overall, it is difficult to judge either system as superior since for most routes and time periods, a dominant control strategy could not be identified. This may be supported by the period-combined confidence interval analysis that did not show a statistically significant control effect on any measure-route combinations.

Previous analysis investigated performance measures on end-to-end type routes. To cover the study area in a more complete fashion, the performance of side street originating traffic was examined based on the random route data. Speeds on random routes and fixed routes were compared and it was found that side street originating travel runs were generally slower under ACTRA. To examine the control system change effect on random routes, binary tree models were developed for the full data set and each time period data subset. The utilized independent variables were, control system type, time period, and geometric conditions, with travel time observations the responses. The control system change appeared in the entire data tree results but its contribution to model accuracy improvements is very small. Among time period groups, the control system change had a statistically significant effect on travel time in only PM peak (17:00~19:00) group. On the other hand, the fixed route data analysis showed that control strategies were not significant on end-to-end type routes in the same period.

The last part of this research compared two control systems using trip time and stop time relation under the two-fluid model theory. After trip times and stop times were compared at disaggregate period-route groups, the two-fluid parameters were estimated and interpreted. At the initial interpretation, discrepancy of superiority was found between the disaggregate group level comparisons and the model interpretation based only on estimated parameters. At the disaggregate level, SCATS decreased trip time and stop time in more groups based on the fixed route data and ACTRA performed better in more groups in terms of stop time based on the random route data. However, based on the estimated two-fluid model parameters, SCATS increased trip time faster in the overall range of stop time for the fixed routes and SCATS decreased trip time in any level of stop time for the random routes. This discrepancy may be because the two-fluid approach places higher weight on higher valued groups. A new interpretation that combines the disaggregate and two fluid model approach was presented. Under this approach, the curve defining trip time versus stop time relation is bounded by traffic conditions and it moves and changes its shape by the control strategy change. Based on these curves, the fraction of moving vehicles in the network can be obtained using the model assumption. As this measure is defined by all time periods and routes data, it can be used as a system-wide performance indicator. Based on this fraction, under SCTAS about 10% more vehicles were moving on the fixed routes when the network was congested and 15% to 20% fewer vehicles were moving on the random routes depending on traffic concentration levels.

Through overall results of this research, it was found that SCATS produced a less extreme shape of travel time distribution, possibly due to the adaptive feature, but that it did not make statistically significant changes in the selected overall analysis measures. Also, it was found that the results of the performance evaluation can vary depending on the measures selected or the study period and location. The proposed system-wide measure may be a useful arterial network performance indicator when analysis categories need to be combined.

In a policy perspective, the findings in this research imply that the design and evaluation of a traffic control system are in many ways a function of the performance measures chosen as critical. Different measure selections may result in different designs and control strategies being selected as preferred. Thus, the selection of performance measures should be based on the interests of the road users, traffic engineers, and local authorities for a given area.

Contributions

This research proposed novel concepts to evaluate an arterial traffic control systems. Those concepts include test vehicle routing and automated data processing in data collection efforts; and measures that have not been actively covered in the existing studies. To apply the proposed measures, relevant statistical methods were also presented. The contributions of this research to related transportation engineering fields are listed as follows.

- An automated GPS test vehicle data reduction algorithm and a travel time database that provides flexibility in the selection of segments in the travel time analysis were proposed.
- A data collection method to capture side street traffic performance on a signalized major arterial was presented.
- It was shown that adaptive traffic control and pre-times time-of-day control may have different travel time distribution forms.
- A procedure that adopts reliability measures for the evaluation of an arterial traffic control system was presented. The procedure includes a non-parametric method for the statistical test of control effects.
- Trip time versus stop time relationship under the two-fluid model theory was applied and improved to present a system-wide performance measure of an arterial network.

Limitation and future work

The scope of this research was limited to ACTRA and SCATS control that were or are operating a fifteen intersection system on Atlanta Road, Paces Ferry Road, and Cumberland Parkway in Cobb County, Georgia. The proposed procedures based on the data from different adaptive control systems in different areas may lead to different conclusions. Therefore, to provide generalized results for the given adaptive control system additional data set from other signal networks need to be included. For example, if the tree model result (a new control system performance evaluation based on the shape statistics of the before control system) in the later part of Chapter 4 is generally applicable, the model or the underlying mechanism may be a useful tool to pre-evaluate an adaptive traffic control system without any investment in a pilot study.

The study results were based on the data collected in clear weather and non-incident conditions. However adaptive traffic control may be more beneficial in incident or non-recurrent congestion conditions, in which the adaptive feature may be more effective. To collect the data in non-typical conditions such as incidents, special events, and adverse weather, a simulation study is required. Simulation models in the market use emulated traffic controllers. As emulated controllers may not reflect real control schemes in the field, a hardware-in-the-loop simulation system may be needed to collect realistic travel time data. In such a system, traffic is generated by the simulator but the traffic control schemes are provided by real controllers. Between them an interface device resides to transfer detector calls from the simulator to the controllers and signal head information from the controller to the simulation. A simulation study provides an additional advantage over a study based on field travel time data. The data can be generated from identical conditions as many times as the time budget allows, so the sample size limitation issue may be better addressed.

APPENDIX A. DATA COLLECTION AND REDUCTION

The following discussion of the data collection and reduction efforts is reproduced with the permission of TRB from *Transportation Research Record: Journal of the Transportation Research Board, No. 1978,* Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 160-168. None of this material may be presented to imply endorsement by TRB of a product, method, practice, or policy.

Practical Procedure to Collect Arterial Travel Time Data Using GPS Instrumented Test Vehicles

Michael Hunter, Seung Kook Wu, and Hoe Kyoung Kim

ABSTRACT

Arterial streets are interrupted flow facilities that balance two purposes: serving through trips and providing commercial and residential access to adjacent land. A dominant factor in urban arterial street operations is the presence of traffic signals, which govern the flow of vehicles that may enter and exit an arterial segment. Consequently, the performance of an arterial street is predominately influenced by delays incurred at traffic signals, with measures of effectiveness (MOEs) primarily a function of the performance at the arterial segment level. This paper presents a practical procedure to collect and analyze GPS-based travel time data that readily reflects measures of performance for both segments and extended arterial sections. Underlying this procedure is an assumption that both average travel speed and average intersection approach delay can be calculated as a function of arterial segment travel time, resulting in travel time as a primary field measurement utilized for gauging arterial performance. The procedures developed include both field data collection techniques that center on GPS technologies and algorithms for processing the gathered GPS-based travel time data.

INTRODUCTION

Urban arterial streets are interrupted flow facilities that balance two purposes: serving through trips and providing commercial and residential access to adjacent land [1]. They tend to have high traffic volumes, intermediate to high operating speeds, and frequent connections with other arterials and collectors. A dominant factor in urban arterial street operations is the presence of traffic signals, which govern the flow of vehicles that may enter and exit an arterial segment. Consequently, the performance of an arterial street is predominately influenced by delays incurred at traffic signals, with measures of effectiveness (MOEs) primarily a function of the performance at the arterial segment level. The *Highway Capacity Manual 2000* defines level of service over an extended section of urban arterial street (one or more miles) based on the average through travel speed and over shorter distances by intersection-level measures such as control delay at signalized intersections [1]. The intent of this paper is to present a practical procedure to collect and analyze GPS-based travel time data that readily reflects measures of performance for both intersection-to-intersection arterial segments and extended arterial sections.

Underlying this procedure is the recognition that both travel speed and intersection approach delay may be calculated as a function of arterial segment travel time. There are currently three primary methods for field collection of travel times: manual, distance measuring instrument (DMI), and global positioning system (GPS) [2]. The manual method is both labor-intensive and susceptible to human errors. DMI technology can provide accurate and reliable travel times, although it requires a significant increase in equipment investment and maintenance [3, 4]. GPS technology gathers time-position data based on the time difference of digital radio signals received from several GPS satellites. Originally developed for military applications, the ability of GPS technology to locate and track objects anywhere on the earth has led an increasing number of nonmilitary personal, commercial, and research uses [2].

Both DMI and GPS technologies can lead to significant reductions in labor costs and human errors compared to manual methods. An advantage of GPS over DMI technology is that GPS instrumentation is typically vehicle independent. That is, the typical GPS field data collection system consists of a GPS receiver and a portable palmtop (PDA) or a laptop, which may be easily moved between vehicles, unlike DMI technology which requires permanent equipment installation to a dedicated data collection vehicle. Furthermore, GPS data can be easily integrated with the geographic information system (GIS) environment, allowing for powerful analysis and presentation abilities. However, GPS also has several potential drawbacks not encountered with DMI technology, including multi-path error, lack of satellites, and poor satellite positions that can result in reduced ability (or even inability) to conduct a travel time study in certain areas or at certain times of day [5, 6].

Recently, the Georgia Institute of Technology conducted a study to evaluate a newly installed traffic signal control system on an urban arterial corridor, with GPS-based travel times as the primary data collected. As part of this evaluation, a practical procedure to collect arterial travel time data using GPS instrumented vehicles was developed. The procedures developed include both field data collection techniques that center on GPS technologies and an algorithm for processing the gathered GPS-based travel time data. This paper provides a review of the developed procedures.

FIELD DATA COLLECTION

There are several important steps that must be completed prior to gathering GPS field data: configuring a test vehicle, selecting travel time routes, creating driver (data collector) instructions, determining necessary sample size, and conducting a pilot study. This discussion provides a review of the procedure used as part of the Georgia Tech study. For more detailed recommendations on field data collection procedures readers are referred to the *Travel Time Data Collection Handbook* [2] or other similar references.

Test Vehicle Configuration

The typical GPS system mounted in a test vehicle consists of a PDA or laptop, a GPS receiver, an external antenna, and a power cable. Satellite signals are received by the antenna, processed by the receiver, and stored in the laptop or PDA. The GPS antenna should be attached on the driver's side roof as this will help minimize multi-path error, e.g., the interruption of satellite signals by objects such as vegetation or buildings [5]. A power cable connecting the PDA or laptop to the vehicle cigarette lighter jack is essential to avoid potential loss of data due to low battery power. Current Georgia Tech data collection efforts use HAiCOM 303E Multi-Mode Foldable GPS Receivers, which have a stated positional accuracy of 10m with 95% confidence interval. PDA model HP iPAQ h2215 is used for storing data and the JAMAR GPS2PDA (PDA software) program provides the interface to record the GPS data stream. With this system, time, speed, latitude, longitude, horizontal dilution of precision (HDOP), and number of satellites are recorded at one-second intervals. In addition to the GPS equipment, a log sheet should be provided to each driver to record start time, end time, route ID, and any comments (i.e., incidents, driver data collection mistakes, construction, etc.) for each run. In the Georgia Tech study the log sheet has proven extremely useful in identifying driver and software errors in the data reduction phase and maintaining clear records of the data collection process.

Route Design

Most urban arterial streets have coordinated signal systems that facilitate through movement, particularly after signal timing optimization strategies are implemented. Thus, a test vehicle conducting end-to-end travel time runs has a high likelihood of predominantly sampling vehicles in the through green band. For longer arterial sections where the HCM-defined LOS based on through vehicle movement is of interest, end-to-end travel time runs may provide reasonable data. However, when attempting to determine intersection approach performance, it is likely that end-to-end travel time runs will result in a biased measurement of delay as vehicle origin-destination paths that tend not to be in the green band will be underrepresented. For example, end-to-end test vehicle travel time data may not reflect the delays incurred by traffic originating from an upstream intersection side-street that has not yet entered the through band. Sampling only vehicles from the upstream through movement may result in significantly higher or lower estimates of the true approach delay [4]. End-to-end runs also provide no information on side-street approach delays. To overcome these deficiencies, two different route types are recommended: fixed and random routes. For fixed routes, drivers are instructed to travel along the given routes based on a path through the entire corridor (i.e., end-to-end travel time runs). For random routes, drivers are given a series of randomly selected origin-destination intersection pairs within the study corridor, with each travel time run beginning and ending on O-D intersection side streets. Ideally, the random routes should be distributed according to the origin-destination matrix of all vehicles in the study area. While the primary interest of this paper is the data collection and processing procedures, it is crucial that careful consideration be given to the potential biases introduced by different sampling procedures (i.e., different travel time run routes). Future companion papers to this work will present a detailed discussion of these issues, supported by extensive real-world data.

Driver Instruction

The safety of the individuals undertaking the data collection and all road users must be of primary concern in any travel time study. To help ensure safety, test vehicle drivers should clearly understand their designated route(s) and data collection equipment use prior to beginning recorded data runs, thereby avoiding any data collection related distractions while driving.

Sample Size

Sample size should be sufficient for the mean travel time calculated from the collected data to have statistical significance. As sample size is well covered in other resources, for example, Tuner et al. [2], it is not reviewed here. The reader is strongly encouraged to review sample size material before undertaking any data collection effort.

Pilot Study

To avoid confusion, errors, and the unnecessary loss of data, it is important that a pilot study be conducted. A pilot study will serve to test all devised procedures and familiarize the data collection team with the proposed process. For example, the pilot study can accomplish the following:

- Confirm selected route starting/ending locations to provide safe maneuvering for test vehicles.
- Confirm applicability of the utilized GPS hardware and software in different test vehicles along the set routes (i.e., is there any significant scattering or occlusion, loss of satellites, etc. that may affect the GPS reliability).
- Ensure driver instructions are clear and understandable.

- Provide field estimation of route travel times, allowing for fine tuning of the data collection plan.
- Familiarize drivers with equipment, data collection log, and travel routes.

The pilot study can provide a very useful opportunity for debugging and revising the data collection protocols prior to the full scale data collection effort. For example, in the Georgia Tech study, the GPS interface used contained a function that required the driver or a data collection assistant to press a button on the PDA at the moment the test vehicle passed through the subject intersection. After several runs, most of the individuals responsible for interacting with the PDA reported feeling motion sickness. Data collector complaints continued even when only brief glimpses at the PDA were taken. From this pilot study, it was recognized that it was necessary to develop additional post-data collection processing algorithms. This new process relieved the need for any interaction with the GPS equipment other than starting and stopping the GPS data collection at the beginning and end of each run.

GPS DATA PROCESSING

The goal of this GPS data processing procedure is the determination of link-based travel times. It is assumed that the GPS data are collected according to the data collection procedure presented in the first portion of this paper, and thus a unique data file exists for each travel time run. At a minimum, the raw data file should contain a row of data for each GPS point (i.e., each second of data) containing the time stamp, latitude, longitude, speed, horizontal dilution of precision (HDOP), and number of satellites. Additional data provided by a GPS receiver may include altitude, heading, vertical dilution of precision (VDOP), positional dilution of precision (PDOP), etc.

Initial Data Processing

The first step in the data processing is to add a run ID to each GPS data point and assign a unique ID to every intersection and route starting/ending location. The run ID is coded to reflect the date, route ID, and cumulative run number. For example, 1104043005 represents travel run 5 (last three digits) for route 3 (seventh digit) on November 4th 2004 (first six digits). These IDs are essential for comparing GPS data files with driver log sheets and maintaining project organization, particularly when large numbers of runs are conducted over multiple days. Intersection and route starting/ending location IDs are simply consecutive numbers. In addition to run IDs, it is also necessary to add the starting/ending location identifiers to each GPS point as these data are required by the algorithm presented later in the paper.

Error Checking

Prior to data analysis, it is critical to implement a thorough error checking procedure. The first step in the error checking process is to address driver errors. Driver errors are primarily identified through notations made on the driver log sheets. For the Georgia Tech study, driver errors fell into three primary categories: starting data collection before initialization of GPS system, missing a turn on the designated travel route, and failing to stop GPS data recording between runs. The data corresponding to runs with the first two types of errors were removed from further consideration, and the third error was addressed by splitting the combined runs into two files containing the individual travel time runs. In addition to driver errors, travel runs in which drivers noted an incident on corridor should be separated from the primary analysis files, although these runs should be maintained for potential incident related analysis.

After addressing driver-related errors, the remaining data must be scanned for potential GPS-related errors. Ogle et al. provide a detailed discussion of the sources of GPS error [6]. Based on these error sources and the pilot study results, the following criteria were developed to identify potentially erroneous data points: distance from the previous point, speed change from the previous point, HDOP, and number of satellites. The distance between consecutive points, speed change, and HDOP criteria each require user judgment and may change based on study conditions. Guidance for setting these criteria are presented next, followed by the procedure used to address potential error points.

Distance between Consecutive Points Criteria

The critical value for this criterion is based on the maximum speed reported the test vehicle drivers. For example, drivers in the Georgia Tech study stated their maximum speed during a travel run to be approximately 50 mph. To allow for some error in driver perception and reasonable GPS speed errors, a maximum speed of 55 mph was selected. Thus, a critical value of 80.67 feet (the distance traveled at 55 mph in one second) was set as the maximum allowable distance between consecutive GPS points. Where the distance between two consecutive GPS points were over 80.67 feet, the latter GPS point was labeled as a potential error point. Post-analysis of processed data showed that less than 0.18% of the total data points collected fell above this critical value.

Speed Change Criteria

The speed change error criterion is defined by maximum acceleration and deceleration rates as these represent the possible speed change in a given time period (one second in this study). Where acceleration and deceleration violate the set criteria, the successive GPS points should be regarded as potential error points. The values ultimately chosen in this study were 10.76 mph/s and -7.64 mph/s for acceleration and deceleration, respectively. Initially, the acceleration and deceleration values were based on the *Traffic Engineering Handbook* [7] and *A Policy on Geometric Design of Highways and Streets* [8], however the values listed in these references were adjusted based on an analysis of the points identified as erroneous. As most travel time studies are typically conducted by only a few drivers acceptable acceleration and deceleration criteria are highly dependent on the test vehicle driver characteristics, thus it is highly recommended that reasonable values be fine tuned for each travel time study. Final selection of criteria relies on the analyst's judgment, considering tradeoffs between the likelihood of a data point being erroneous, impact of the potential error on the analysis, and the impact of potentially eliminating accurate data. Final analysis of the processed data showed that less 0.09% and 0.05% of the data violated the final acceleration and deceleration criterion, respectively. As part of these criteria, failure of the GPS to determine a speed was also checked. The utilized GPS equipment reported this by listing -1 as the speed value.

HDOP Criteria

HDOP reflects the quality of the geographic configuration of satellites at the moment a GPS point is recorded [5]. Desirable HDOP values are below 4, and values above 8 should not be used [9]. Determining the HDOP cutoff value requires balancing between desired data accuracy and loss of potentially accurate data. In this study, the critical value selected for HDOP was 4. Preliminary analysis of the data collected in this study found that 94.22% of the GPS points had an HDOP value less than 2 and 98.73% had a HDOP value less than 4. While a higher HDOP cutoff (e.g., 8) may be justified, particularly as those points with HDOP values between 4 and 8 that appeared questionable were likely also identified by the other criteria, the more conservative HDOP value of 4 was used.

Number of Satellites Criteria

The number of satellites criterion must be set at four or more to satisfy the minimum requirement for GPS technology to solve the four simultaneous equations required to determine positional information (x, y, and z coordinates) and clock bias [10]. Less than 0.25% of the GPS points collected in this study had fewer than four satellites.

Potential Error Point Initial Screening

After data points are identified as potential errors, the following procedure was implemented before processing the data.

- If an error point is isolated, the corresponding row in the data file is replaced with a new row with values interpolated from the proceeding and following data points.
- If a significant number of error points exist in a single run, the run is superimposed on the digital map and reviewed visually. Unless the visual inspection is able to confirm the accuracy of these points or there exists a reasonable ability to interpolate corrected points, the entire run is eliminated from further analysis.
- If the number of potential error points is low but corrected values may not be reliably interpolated, the run is not eliminated, and an error indicator is added to the data fields of each potential error point. The algorithm presented later has a

filtering step to ensure that points marked as potential errors are not incorporated into the analysis.

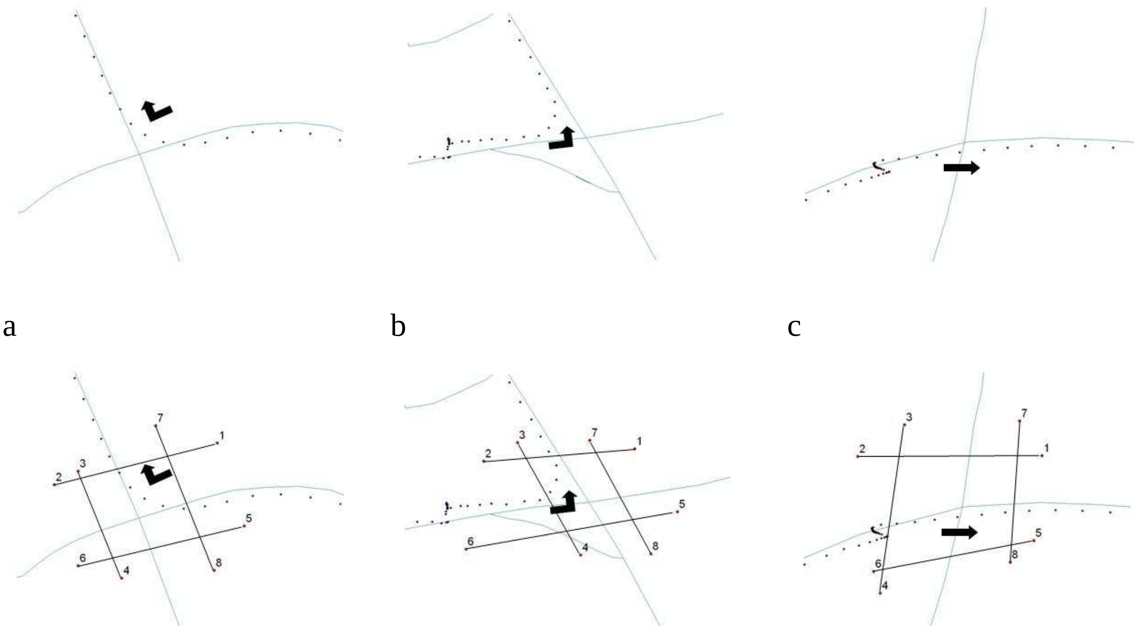
As seen, only the runs with a high number of potential errors are eliminated, while those with a low number of potential errors are flagged. This is done to achieve balance between elimination of entire runs where the vast majority of data points are accurate and reduction of potential errors that may be introduced by even a few erroneous points. The cutoff point utilized for any study must be based on analyst judgment. For the Georgia Tech study, typical runs were on the order of ten minutes (i.e., 600 one-second data points). A value of 10% of the total number of points identified as potential errors was considered significant and warranted eliminating the entire run.

Travel Run Intersection Passing Time Identification (TRIPTI) Algorithm

The Travel Run Intersection Passing Time Identification (TRIPTI) algorithm is utilized to identify the time at which a test vehicle completes its pass through each intersection of a travel time run. The TRIPTI algorithm results may then be utilized to determine intersection-to-intersection travel times. The algorithm is designed such that the subsequently determined intersection-to-intersection travel times will include the delay experienced while traversing the link and the delay incurred at the downstream intersection. To ensure that the downstream intersection delay is assigned to the proper arterial segment, travel time is calculated from a reference line just past the upstream intersection to a reference line just past the downstream intersection.

Thus, prior to utilizing the TRIPTI algorithm, it is necessary to create an array containing the set of reference points and reference lines (see Figure 1) for each intersection that may be used to identify the location at which a vehicle is determined to have successfully traversed the intersection. In Figure 1, three different typical intersections (1a, 1b, and 1c) are shown with second-to-second GPS points from sample travel runs superimposed on a digital map. Figures 1d, 1e, and 1f show the corresponding reference points and line segments for 1a, 1b, and 1c. The right turn movement (1a) demonstrates non-stop travel, identified by the relatively smooth spacing between data points. In contrast, the left (1b) and through (1c) movements demonstrate test vehicles that are stopped in a queue prior to successfully traversing the intersection. A stopped vehicle is identified by the clustering of GPS data points.

Reference points (Figures 1d, 1e, and 1f) must be placed such that a line segment (i.e., reference line) connecting them will intersect the travel path of any vehicle exiting the intersection from the subject approach. Reference lines are placed to ensure that vehicles have crossed through the intersection. For example, when departing northbound (Figure 1e), a vehicle must cross reference line 1-2. Currently, reference points and lines are manually constructed. It is helpful to complete this task inside a GIS environment. For example, in Figure 2, GPS travel run points are superimposed on an aerial photo, offering a visual guide in the determination of reference points. Placing of reference points may be an iterative process. Upon initial execution of the TRIPTI algorithm, additional fine-tuning of the reference point placement may help reduce identified potential errors. Companion efforts currently underway are investigating the placement of references lines, or the processing of departing vehicle trajectories, to more directly allow for the capture of delays due to acceleration.



a b c

d e f

FIGURE 1 Typical GPS Points Representing a Right Turn (a, d), Left Turn (b, e), and Through (c, f) Movement.

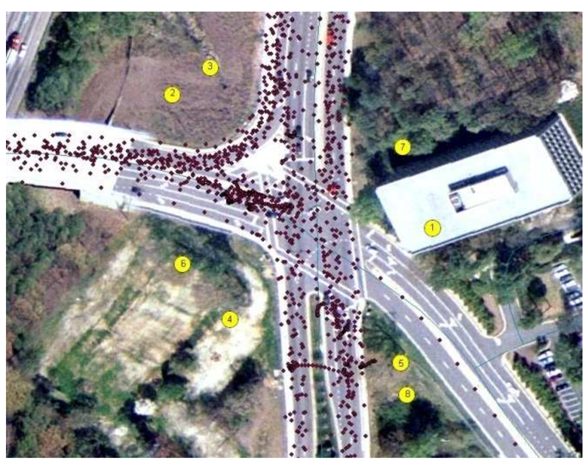


FIGURE 2 Illustrative Example of Locating Reference Points (Numbered Circle) Aided by an Aerial Photo and GPS Points Superimposed in a GIS Environment.

TRIPTI Algorithm

As stated, the purpose of the TRIPTI algorithm is to determine the time at which a vehicle passes each intersection reference line during a travel time run. Given these passing times, the determination of segment travel times is straightforward. In the algorithm development, it is assumed that the study corridor (or network) contains *J* intersections where *j* denotes a unique intersection, thus $j = 1, \ldots, J$. Each travel run consists of *I* consecutive second-by-second data points and passes through L intersections, thus $i = 1, \ldots, I$, and $l = 1, \ldots, L$. A travel time run is assumed not to pass through the same intersection more than once, and not all intersections are required to be visited in a travel time run, i.e., $L \leq J$. This flexibility allows the TRIPTI algorithm to be utilized for multiple paths within the corridor. To implement the TRIPTI algorithm, the following variables are defined:

P_i = vector containing latitude and longitude of the data point *i*

C_j = vector containing latitude and longitude of the center of intersection *j*

d_{ij} = Distance from P_i to C_j

d_j^* = Minimum d_{ij} over all *i*

r_j = critical threshold for determining if vehicle passes through intersection *j*

$[TR_l^d]$ = Matrix containing travel time run route data, where:

TR_l^1 = the time at which the test vehicle passes closest to the center (C_j) of the l^{th} intersection of the travel time run route

TR_l^2 = the intersection *j* associated with TR_l^1

$[TRE_m^d]$ = Matrix containing travel run intersection path exit point data where:

TRE_m^1 = exit time (i.e., vehicle crosses reference line) at intersection *m*

TRE_m^2 = the intersection *j* associated with TRE_m^1

$h^q(a,b)$ = Matrix containing the reference point vectors ($q = 1, 2$) at intersection *a* for a vehicle traveling to intersection *b*

$Z_i(j)$ = Distance function used to find the point *i* nearest to the reference line of intersection *j*

T = The ending location for the travel run, this point is identified in the initial data processing

The TRIPTI algorithm is now presented. The first part of TRIPTI is the travel time run (according to time visited) route to intersection matching. In this process, the algorithm determines the ordered set of corridor intersections that comprise the travel time run.

Route to Intersection Matching

0: Initialize $l = 0$, $t = 0$

1: for $j = 1$ to J

{

$d_{ij} = \left\| P_i - C_j \right\| \quad \forall \text{i}$

Solve $\min_i \{d_{ij}\}$, let t = time stamp of solution point i

If $d_j^* < r_j$, then, $l = l+1$, $TR_l^1 = t$, $TR_l^2 = j$

}

2: Sort columns of [TR_l^d] in ascending order according to [TR_l^1]

$L = l$

$TR_{L+1}^2 = T$

Remarks: In step 1, the series of L intersections that the travel run passes through are identified and stored in the vector [TR_l^2]. The test for intersection inclusion in a route is simply whether at least one GPS point in the travel run data falls within a critical distance, r_j, to the center of the intersection. The r_j value should be fine-tuned for each intersection of the network under study, as intersection geometrics directly impact the expected distance from the intersection center to any traversing vehicle path. In step 2, TR_l^2 is sorted in chronological order, allowing for its use in the next phase of the TRIPTI algorithm. Step 2 also increases the array size of TR_L^2 by one resulting in TR_{L+1}^2, and stores the unique identifier of the ending location in TR_{L+1}^2. The ending location, T, was determined in the initial data processing. The next process of the TRIPTI algorithm identifies the time at which the travel time run vehicle clears each intersection l of the travel route.

Determination of Intersection Crossing Time

0: Initialize $m = 0$, $t = 0$

1: for $l = 1$ to L

{

Let $a = TR_l^2$ and $b = TR_{l+1}^2$

$$Z_i(a) = \frac{\left(h^1(a,b) - P_i\right) \bullet \left(h^2(a,b) - P_i\right)}{\left\| h^1(a,b) - P_i \right\| \left\| h^2(a,b) - P_i \right\|} \quad \forall i$$

Solve $\min_i \{Z_i(a)\}$, let t = time of solution point i and e = error tag value of i

Check vehicle speed less than 5 mph. If yes, set $e = 1$

If $e = 0$, then, $m = m+1$, $TRE_m^1 = t$, $TRE_m^2 = a$

}

Remarks: The Intersection Crossing Time process sets the time of the GPS data point i nearest the exiting reference line of intersection as the time at which a vehicle is said to have completed its traverse of the intersection. The cosine function is utilized to determine the point i nearest the reference line. In this process $Z_i(a)$ is the cosine of the angle formed between the vector from each reference point to point i, for a vehicle traversing intersection a to downstream intersection b. Figure 3 illustrates the angle checked in this process. Since the cosine function has a minimum value at 180º, the point i that minimizes $Z_i(a)$ is also the point closest to the reference line. As part of this procedure, the point i that minimizes $Z_i(a)$ is checked for any error flags identified in the error checking process. An additional error check is also incorporated. As the vehicle is exiting the intersection, its speed should exceed 5 mph. Where this is not the case, the point is a potential error and should be checked through visual inspection. While not shown in this version of the TRIPTI algorithm, one additional check was later incorporated into the determination of the intersection crossing time. For the selected reference points it was found that a vehicle passing through the intersection may not be shown to cross the reference line. This may be a result of reference point placement or offset of GPS data points. Where this was determined to have occurred, the GPS point is identified as a potential error and visually inspected. If a potential error has been identified, the time stamp and information index are not saved. In the travel time analysis, travel time for $l-1$ to l and l to $l+1$ will be combined, where l is intersection a. Future efforts will seek to refine this approach and investigate methods to estimate the traversing point when potential data errors exist.

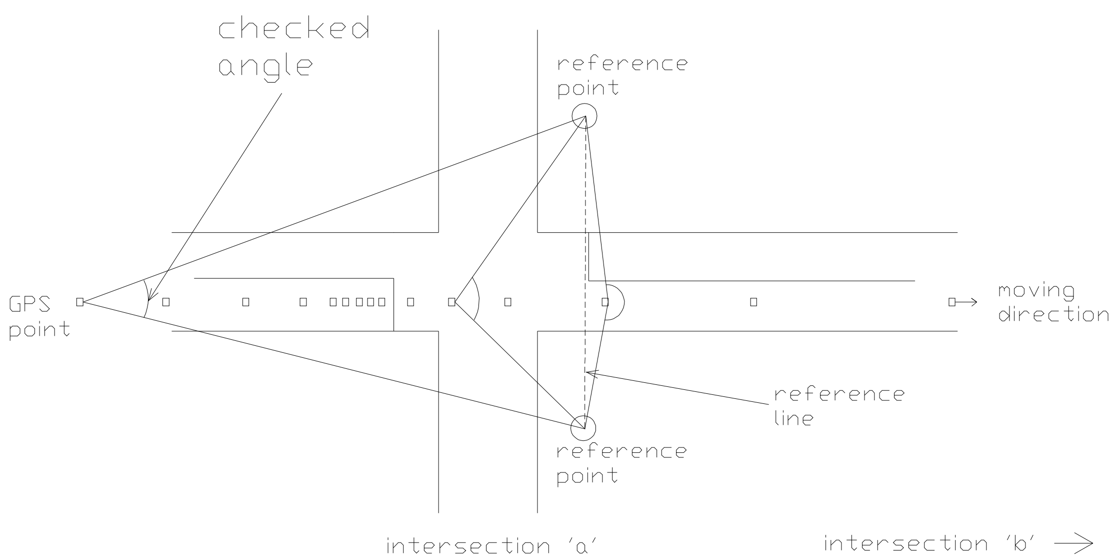
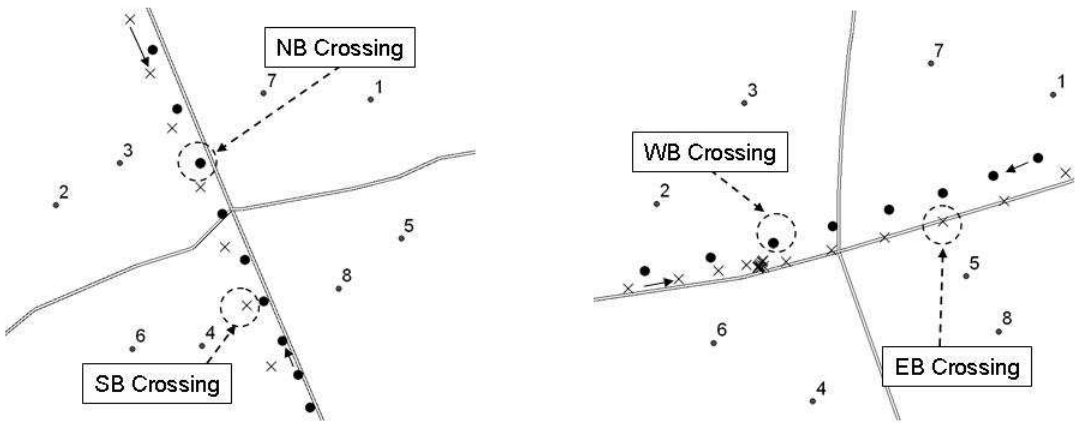


FIGURE 3 Geometric Configuration of GPS Points, Reference Line, and Checked Angle.

The final product of the TRIPTI algorithm is the vectors [TRE_m^1] and [TRE_m^2], the time stamps, and the intersection IDs recorded for each intersection traversed in the travel run, respectively. These vectors are utilized in the travel time database to be presented in a subsequent section.

Example Algorithm Results

For sample segments from two runs collected on the study corridor Figures 4a and 4b show the TRIPTI identified points nearest to the reference line, tagged for visual identification in GIS environment and superimposed on the digital map.



a. Atlanta Road at Jane Lyle Road b. Paces Ferry Road at Spring Hill Parkway

FIGURE 4 Example Results of TRIPTI Algorithm.

Database for Calculation of Statistics

The developed travel time database is a two dimensional array whose cells contain scalar and array data. A cell (*i, j*) in the database contains the specified information for all runs from intersections *i* to *j*. Data fields for each run include run ID, entering time (i.e., the exit time from intersection *i*), exit time (i.e., the exit time from intersection *j*), travel time, day of week, time of day, origin ID, destination ID, number of runs, distance, and free flow time. With each iteration of the TRIPTI algorithm (each travel time run requires a TRIPTI iteration), the database is updated to incorporate the additional travel run data. Based on the output from the TRIPTI algorithm, the database may be used to calculate travel time, average delay, average speed, etc. for *any* two intersections included in the travel runs, not just consecutive intersections. By also including the time and date in the database it is also readily possible to conduct analysis over a specific time period (e.g., AM peak, PM peak, off-peak, etc.) or set of days. This allows for great flexibility in interpreting travel time results, allowing an analyst to consider different corridor segment lengths, from performance between consecutive intersections, to corridor sections incorporating several intersections, to the entire corridor over differing time periods.

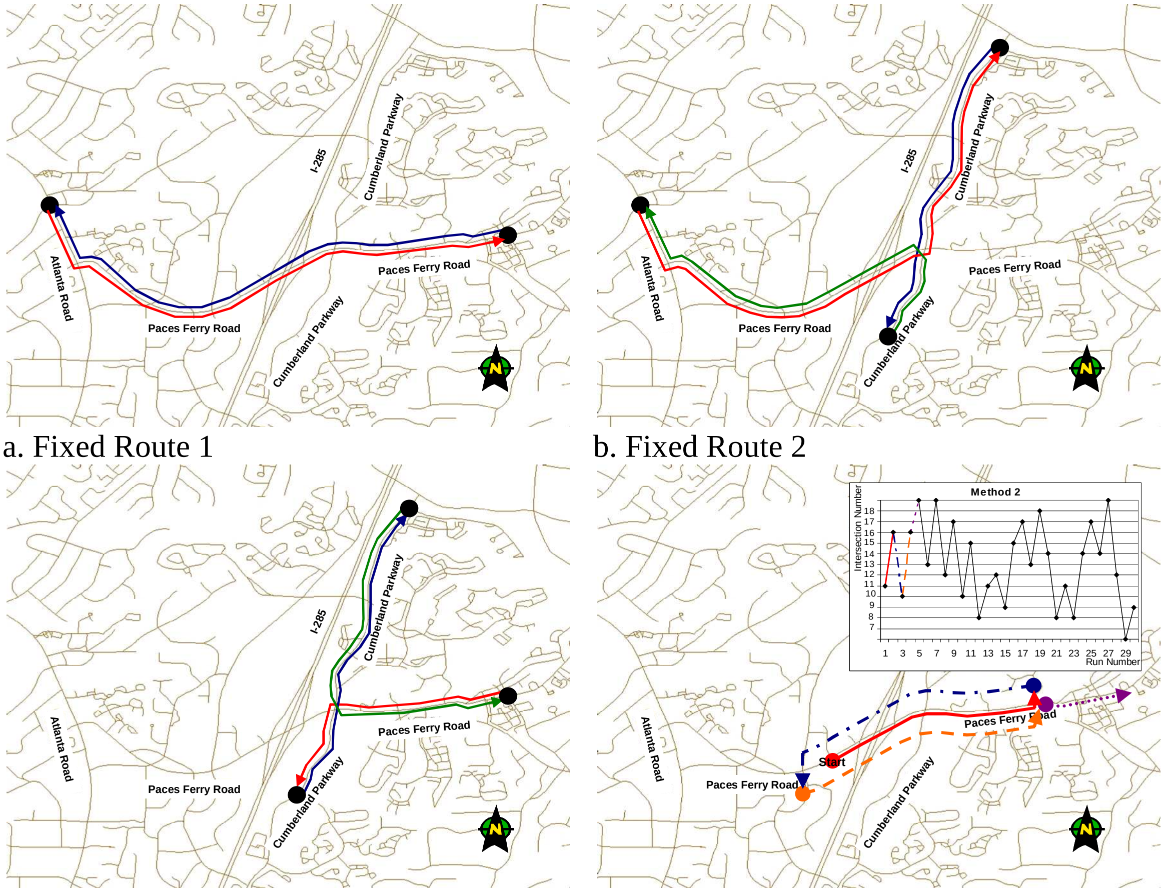
Calculation of Statistics

As stated, the database developed has the advantage of being able to calculate statistics for all possible trips from intersections *i* to *j*. Scripts are written to determine the desired statistic for any cell (*i*, *j*). For example, the mean travel time for cell (*i*, *j*) is calculated as exiting time - entering time. In this calculation, delay at intersection *i* is not included and delay at intersection *j* is included, as expected. Given the cell (*i*, *j*) travel time, it is now a simple matter to determine average speed (travel time / travel distance) and delay (desired travel time - actual travel time). To calculate delay, it was assumed the drivers desired to travel at the posted speed limit, although other rationales for determining desired travel time could certainly be utilized. Numerous other statistics can also be calculated utilizing the database.

APPLICATION OF THE PROCEDURE

The data collection and analysis procedures that have been discussed were utilized to evaluate a signal system installed on 15 intersections (Figure 5) on Atlanta Road, Paces Ferry Road, and Cumberland Parkway in Cobb County, Georgia. Fixed routes and a series of randomized routes were designed for travel time data collection. The fixed routes (Figures 5a, 5b, and 5c) were designed to capture the east-west and north-south directions of travel along with the left turn movements at Paces Ferry Road and Cumberland Parkway. While results are not presented here random routes (Figure 5d) were also selected such that the vehicles path during the data collection period consisted of a series of randomly selected intersection-to-intersection traverses along Paces Ferry Road. For example, at the start of the data collection period a vehicle would begin on the side street of an intersection near the mid-point of the Paces Ferry Road corridor. The vehicle would turn onto Paces Ferry Road heading eastbound or westbound with equal probability. The vehicle would travel two to six intersections, again each distance having an equal probability. Upon reaching the destination intersection the vehicle would randomly turn left or right from Paces Ferry Road. The process would then continue from that side street. Figure 5d shows the first four legs of a randomized set of travel runs, with the insert graph showing a random path consisting of 30 intersection to intersection traverses.

For the Georgia Tech study four different test vehicle drivers participated in the fixed route data collection. Data was collected over six weekdays and four weekend days during the weekday morning peak, weekday morning off-peak, weekday afternoon peak, weekday evening peak, and weekends. The weekend collection times were selected to capture a range from low to high weekend demands. A total of 755 fixed route runs were conducted with 19 runs eliminated in the initial error checking stage, resulting in 736 runs (97.5%) of the original data being processed with the TRIPTI algorithm.



a. Fixed Route 1 b. Fixed Route 2

c. Fixed Route 3 d. Random Route

FIGURE 5 Route Design for Travel Time Data Collection.

The TRIPTI algorithm was used to calculate travel times between every intersection pair that existed within a travel time run. Table 1 gives the mean travel times generated for all traveled origin (*i*) to destination (*j*) intersection pairs before signal improvements were installed. From this table, performance between any pair of intersections may be gauged. The next phase of the Georgia Tech study will include analyzing travel runs conducted after this signal improvements were implemented. With the database developed from the TRIPTI algorithm, it will be possible to readily conduct before and after comparisons on any travel path through the study area.

TABLE 1 Average Travel Time Matrix, Aggregation of All Time Periods for Fixed Routes (seconds)

i\j	1	2	3	4	5	6	7	8T	9	10	11	12T	13	14	15	8L	12R
1	N/A	56.0	91.8	119.9	134.8	157.2	175.9	207.0	235.1	275.4	296.1	321.6	N/A	314.7	335.9	252.9	N/A
2	33.1	N/A	35.8	63.7	78.6	101.0	119.6	148.3	176.4	216.5	238.0	262.4	N/A	261.1	282.4	199.5	N/A
3	77.2	44.0	N/A	28.0	42.9	65.3	83.9	113.2	141.2	181.3	203.0	227.3	N/A	224.5	246.1	162.9	N/A
4	97.8	64.6	20.6	N/A	14.8	37.3	55.9	85.4	113.6	153.7	175.3	199.7	N/A	196.7	218.1	135.0	N/A
5	113.2	80.1	36.1	15.6	N/A	22.4	41.0	71.0	99.0	138.9	160.6	185.1	N/A	180.9	202.2	119.2	N/A
6	125.2	92.1	48.1	27.5	11.9	N/A	18.6	46.9	75.0	114.6	136.3	161.0	N/A	160.5	182.4	98.9	N/A
7	147.9	114.9	70.9	50.4	34.9	23.0	N/A	27.8	55.9	95.4	117.3	141.9	N/A	142.4	164.3	80.9	N/A
8	183.4	150.3	106.3	85.6	70.4	58.2	35.3	N/A	31.1	70.5	94.0	114.1	33.1	59.7	81.7	N/A	110.5
9	222.0	188.4	144.5	124.3	107.4	95.4	75.1	51.1	N/A	39.3	64.9	86.0	129.7	163.0	182.0	92.5	76.2
10	240.1	206.5	162.5	142.4	125.5	113.4	93.1	69.2	18.9	N/A	25.9	47.0	149.9	179.0	198.0	113.0	37.1
11	271.3	237.6	193.6	173.5	156.6	144.7	122.9	99.6	51.6	32.6	N/A	19.7	184.9	196.0	215.0	147.5	11.6
12	299.0	265.1	221.1	201.2	184.2	172.4	150.6	127.6	79.7	60.9	28.4	N/A	213.3	211.0	230.0	176.1	N/A
13	281.8	249.6	205.6	184.4	171.6	159.8	133.4	68.6	N/A	N/A	N/A	N/A	N/A	125.4	148.2	85.9	N/A
14	N/A	N/A	N/A	N/A	N/A	N/A	N/A	119.4	169.9	209.0	234.5	N/A	147.8	N/A	21.6	135.6	246.1
15	N/A	N/A	N/A	N/A	N/A	N/A	N/A	155.8	206.0	245.4	270.9	N/A	183.9	35.5	N/A	171.4	282.5

Note: 8T: Paces Ferry Road Eastbound / Westbound through movements at intersection 8
12T: Paces Ferry Road Eastbound through movement at intersection 12
8L: Paces Ferry Road Eastbound / Westbound left turn movements at intersection 8
12R: Paces Ferry Road Eastbound right turn movement at intersection 12

CONCLUSIONS

This paper describes a procedure developed for travel time data collection on urban arterial streets using GPS instrumented test vehicles. The procedures developed include both field data collection techniques that center on GPS technologies and algorithms for processing the GPS-based travel time data. The field data collection procedure includes outlining equipment needs (PDA or laptop, GPS receiver, external antenna, and power cable), designing the travel time study, driver instructions (safety, equipment, data collection routes, and data log), and a pilot study.

Initial data processing and error checking procedures are recommended. The initial data processing provides identifiers to the data sets, allowing for the management of the potentially very large data sets that can be created through GPS efforts. The error checking procedure is aimed at removing and identifying erroneous data points, resulting from either driver or equipment sources. Potential GPS error identification guidelines were developed for the distance between consecutive data points, GPS point speed change, HDOP criteria, and number of available satellites.

Once the data has been collected, the final data processing consists of three main processes: the TRIPTI algorithm, database development, and statistics calculation. The TRIPTI algorithm identifies the time a vehicle passes through each intersection in a travel time run. The database stores the travel time and associated GPS data for all intersection-to-intersection vehicle runs. The database can then be utilized for the calculation and analysis of relevant statistics over differing study area sections and time periods. Based on the output from the TRIPTI algorithm statistics for *any* intersection origin-destination pair included in the travel runs, not just consecutive intersections, may be determined.

This allows for great flexibility in interpreting travel time results, allowing an analyst to consider different corridor segment lengths, from consecutive intersections to the entire corridor, over multiple time periods. However, the overall data processing procedure still requires considerable user interaction (visual error checking, development of reference points, etc.). Also, this procedure is limited to travel times based only upon the time at which a vehicle passes an intersection. Thus, this procedure utilizes a very small subset of the GPS data. To generate non-travel time based performance measures such as percent time stopped, time under/over a specific speed, etc., all of the GPS data from each run would be utilized. This level of GPS data usage would require additional quality control checking for GPS point wander and other potential issues. Future efforts will be dedicated to addressing these more intensive GPS data use statistics and to reducing user interaction required to process data. In addition, studies will be conducted to further explore the error criteria and the sensitivity of performance measures to selected error criteria bounds.

REFERENCES

1. *Highway Capacity Manual 2000 (HCM 2000)*. TRB, National Research Council, Washington, D.C., 2000.
2. Turner, S.M., W. L. Eisele, R. J. Benz and D. J. Holdener. *Travel time data collection handbook*. Texas Transportation Institute, 1998.
3. Quiroga., C.A. and D. Bullock. Measuring control delay at signalized intersections. *Journal of Transportation Engineering* 125(4), 1999, pp. 271-280.
4. Turner, S.M. Advanced techniques for travel time data collection. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1551,* TRB, National Research Council, Washington, D.C., 1996, pp. 51-58.
5. Czerniak, R.J. *NCHRP Synthesis 301: Collecting, Processing, and Integrating GPS Data into GIS*. Transportation Research Board, National Research Council, Washington, D.C., 2002.
6. Ogle, J., et al. Accuracy of global positioning system for determining driver performance parameters. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1818*, TRB, National Research Council, Washington, D.C., 2002, pp. 12-24.
7. *Traffic Engineering Handbook (5th ed.)*. Institute of Transportation Engineers, Washington, D.C., 1999.
8. *A Policy on Design of Highway and Streets (4th ed.),* American Association of State Highway and Transportation Officials, Washington, D.C., 2001.
9. GPS-Explained. www.kowoma.de/en/gps/errors.htm. Accessed in July 2005.
10. Logsdon, T. *Understanding the Navstar: GPS, GIS, and IVHS (2nd ed.).* Van Nostrand Reinhold, New York, 1995.

APPENDIX B. MAXIMUM LIKELIHOOD ESTIMATION

In this study the best normal, log-normal, and gamma distributions to fit the data were obtained by maximum likelihood estimation, which is one of the best methods to estimate unknown parameters of a distribution *(68)*. Suppose that X is a random variable with probability density function, f(x, ɵ), in which ɵ represents one or more parameters of f( ). Let X_1, X_2, …, X_n be the observations in a random sample. Then, the likelihood function is written as

$$L(\theta; x) = \prod_{i=1}^{n} f(\theta; x_i).$$

It should be noted that as the observations (i.e. x) are fixed, the likelihood function is now a function of ɵ. The maximum likelihood estimator (MLE) of ɵ is the value that maximize the L( ), meaning that obtained estimator maximizes the probability of occurrence of the sample x. To efficiently apply optimization algorithms, often the function is taken by the logarithm. This transformation turns the original form to a linear sum but does not change the maxima. The log-likelihood function, l(x, ɵ) is then given by

$$l(\theta; x) = \sum_{i=1}^{n} \log f(\theta, x_i).$$

More details of the method can be found in *(66)*.

APPENDIX C. KOLMOGOROV-SMIRNOV TEST

This test was used in this research when an empirical cumulative distribution function (CDF) was tested against a theoretical CDF for goodness-of-fit. Let X_1, X_2, …, X_n be a sample from a population with an unknown continuous CDF. Let $f_n(x)$ and $f_0(x)$ be the empirical CDF from the sample and a theoretical CDF respectively. The tested null hypothesis, H_0 is $F(x) = F_0(x), (\forall x)$. The alternative hypothesis H_1 is $F(x) \neq F_0(x)$. The test statistic is given by $\sqrt{n}D_n = sup_x \sqrt{n}|F_n(x) - F_0(x)|$. If the data are sorted, the calculation can be written as

$$\sqrt{n}D_n = \sqrt{n}max\{max_i|F_n(X_i) - F_0(X_i)|, max_i\, |F_n(X_{i-1} - F_0(X_i)|\},$$

where, X_{i-1} is 0 when i=1.

Kolmogorov showed that under H_0,

$$P\left(\sqrt{n}D_n \leq d\right) = 1 - 2\sum_{j=1}^{\infty}(-1)^{j-1}e^{-2j^2d^2}.$$

The critical value of d for the test with 5% significance level makes the above probability 0.95. More details can be referred to *(67)*.

APPENDIX D. GAUSSIAN KERNEL DENSITY ESTIMATOR

A density histogram is a density estimator that spreads the probability mass of an observation uniformly in a bin that the observation belongs to, but it is generally bumpy and may display a different shape depending on the width and boundaries of the bin. A kernel density estimator spreads probability mass smoothly around the observation using a kernel, and thus it is more helpful to see the shape of a distribution. The adopted Gaussian kernel density estimator can be written as

$$\hat{f}(x) = \frac{1}{nh_n}\sum_{i=1}^{n} \emptyset(\frac{x-x_i}{h_n}),$$

where, $\hat{f}(x)$ = Gaussian kernel estimator

n = number of observation

x_i = ith observation

$\emptyset(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}}$

h_n = bandwidth.

The bandwidth controls the spread of the kernel. If it is small, the details of the middle part of a distribution will be highlighted, but the tail part will be bumpy. If it is large, the tail part will be handled better but the characteristic of the middle part may be lost *(67)*. The optimal bandwidth was determined to minimize the sum of the variance and the bias of the density estimator. More details of the Gaussian density estimator can be found in *(66, 67)*.

APPENDIX E. CLASSIFICATION TREE

Building and pruning the tree followed the same procedure for the regression tree model presented in Chapter 6. The only difference is the heterogeneity measure in a node. A regression tree generally uses residual sum of squares but it does not suit for a classification problem. In a node, m representing region R_m with N_m observations, the proportion of class k in node m is

$$\hat{p}_{mk} = \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i = k).$$

The model assigns k(m) to node m, where k(m) is the majority class in node m, that is

$$k(m) = argmax_k \hat{p}_{mk}.$$

With this set-up, classification tree models use one of the following heterogeneity measures *(66)*.

Misclassification error:

$$\frac{1}{N_m} \sum_{i \in R_m} I\big(y_i \neq k(m)\big) = 1 - \hat{p}_{mk(m)}.$$

Gini index:

$$\sum_{k \neq k'} \hat{p}_{mk} \hat{p}_{mk'} = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk}).$$

Cross-entropy (or deviance):

$-\sum_{k=1}^{K} \hat{p}_{mk} log \hat{p}_{mk}$.

The three measures are similar but Gini index and Cross-entropy are differentiable and thus more convenient for optimization *(66)*. The classification tree model in this research used Gini index.

APPENDIX F. RESULTS OF TREE MODEL WITH FULL RANDOM ROUTE DATA SET

The table below summarizes the results of tree model using the entire random route data as the input in Chapter 6. The parameter cp controls tree size in RPART. As cp decreases the tree grows bigger. As seen in Figure 40 and this table, some splits occur at the same time for a cp value.

Sequential split #	Value of cp	Split variable and point	Training error	Prediction error
1	0.273248242	N_int<5.5	0.7267518	0.7728398
2	0.102883032	N_int<2.5	0.6238687	0.6544810
3	0.048489164	t_turn=R	0.5753796	0.6228283
4~5	0.025888011	tod=2,3,5,6 t_turn=R	0.5236035	0.5951490
6	0.017650118	len<0.625	0.5059534	0.5885128
7	0.017594248	N_int<6.5	0.4883592	0.5701966
8	0.015765185	tod=2,3,6	0.4725940	0.5668809
9	0.015182516	N_drv<1	0.4574115	0.5622090
10~12	0.011930525	len=>0.9 N_drv<1 cntl=A	0.4216199	0.5505325
13	0.008925404	len<0.26	0.4126945	0.5400654
14	0.005154486	tod=2,3,5	0.4075400	0.5430052
15	0.004818380	tod=2,3,5,6	0.4027216	0.5456579
16~18	0.004747246	tod=2,6 t_turn=R f_turn=R	0.3884799	0.5452915
19~20	0.004693406	len>=0.815 len<0.45	0.3790931	0.5470391
21	0.004010215	tod=2,4,6	0.3750829	0.5473060
22	0.003689474	f_turn=R	0.3713934	0.5391933

REFERENCES

1. Schrank, D. and T. Lomax. *The 2007 Urban Mobility Report*. 2007.

2. Intermodal Surface Transportation Efficiency Act of 1991 - Summary http://ntl.bts.gov/DOCS/ste.html

3. TEA-21 - Transportation Equity Act for the 21st Century http://www.fhwa.dot.gov/tea21/sumtoc.htm

4. A Summary of Highway Provisions in SAFETY-LU http://www.fhwa.dot.gov/safetealu/summary.htm

5. Cambridge Systematics, Inc. and Texas Transportation Institute. *Traffic Congestion and Reliability*. FHWA, 2005.

6. Cambridge Systematics, Inc., Texas Transportation Institute, University of Washington and Dowling Associates. *Providing a Highway System with Reliable Travel Times, Study 3 - Reliability*. Transportation Research Board, 2003.

7. University of Maryland. *User Determined Attributes of Ideal Transportation Systems: An Empirical Study*. 1966.

8. Small, K. A., R. Noland, X. Chu and D. Lewis. *Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation*. National Cooperative Highway Research Program. 431. 1999.

9. Texas Transportation Institute and Cambridge Systematics, Inc. *Monitoring Urban Freeways in 2003: Current Conditions and Trends from Archived Operations Data*. FHWA, 2004.

10. SHRP 2 Overview. http://gulliver.trb.org/shrp2/SHRPII_About.asp

11. Ruberti, A. *Control Methods in Urban Traffic Areas*. 2004.

12. Klein, L. A. *Sensor Technologies and Data Requirements for ITS*. Artech House, Boston, 2001.

13. Roess, R., E. Prassas and W. McShane *Traffic Engineering*. Pearson Education Inc., Upper Saddle River, NJ, 2004.

14. Lowrie, P. R. *SCATS Sydney, Co-Ordinated Adaptive Traffic System, a Traffic Responsive Method of Controlling Urban Traffic*. Road and Traffic Authority of New South Wales, Australia, 1990.

15. William, R. J. and P. H. Wright. Factors Which Influence Modal Choice. *Traffic Quarterly*, Vol. 28, No. 2, 1974, pp. 271-289.

16. Abdel-Aty, M. A., R. Kitamura and A. P. Jovanis. Investigating Effect of Travel Time Variability on Route Choice Using Repeated Measurement Stated Preference Data. *Transportation Research Record*, Vol. 1493, 1995, pp. 39-45.

17. Small, K. A., C. Winston and J. Yun. *Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability: Implications for Road Pricing*. University of California, Transportation Center, 2002.

18. Lam, T. C. and K. A. Small. The Value of Time and Reliability: Measurement from a Value Pricing Experiment. *Transportation Research Part E*, Vol. 37, 2001, pp. 231-251.

19. Recker, W., Y. Chung, J. Park, L. Wang, A. Chen, A. Ji, H. Liu, M. Horrocks and J.-S. Oh. *Considering Risk-Taking Behavior in Travel Time Reliability*. UCI-ITS-TS-WP-05-4. 2005.

20. Elsayed, E. A. *Reliability Engineering*. Addison Wesley Longman Inc., Reading, MS, 1996.

21. Shaw, T. *Performance Measures of Operational Effectiveness for Highway Segments and Systems*. NCHRP Synthesis 311. 311. 2003.

22. *The Keys to Estimating Mobility in Urban Areas*. Texas Transportation Institute, 2005.

23. Lomax, T., D. Schrank, S. Turner and R. Margiotta *Selecting Travel Reliability Measures*. 2003.

24. Polus, A. *Measurement of Transportation System Reliability: Concepts and Application*. Northwestern University, 1975.

25. Margiotta, R. Travel Time Reliability: Its Measurement and Improvement. *9th World Congress on ITS*, 2002,

26. Iida, Y. Basic Concepts and Future Directions of Road Network Reliability Analysis. *Journal of Advanced Transportation*, Vol. 33, No. 2, 1999, pp. 125-134.

27. Elefteriadou, L. and X. Cui. A Framework for Defining and Estimating Travel Time Reliability. *Transportation Research Board 2007 Annual Meeting CD-Rom*, 2007.

28. *Florida's Mobility Performance Measures Program*. Florida Department of Transportation, Office of the State Transportation Planner, 2000.

29. Ikhrata, H. and P. Michell. Technical Report of Southern California Association of Governments' Transportation Performance Indicators. *Transportation Research Record*, Vol. 1606, 1997, pp. 103-114.

30. Jackson, D. D. *Reliability as a Measure of Transportation System Performance*. Texas A&M University, 2000.

31. Lomax, T., S. Turner, G. Shunk, H. S. Levinson, R. H. Pratt, P. N. Bay and G. B. Douglas. *Quantifying Congestion*. NCHRP Report 398. 398. 1997.

32. Travel Time Reliability: Making It There on Time, All the Time http://ops.fhwa.dot.gov/publications/tt_reliability/TTR_Report.htm

33. Polus, A. A Study of Travel Time and Reliability on Arterial Routes. *Transportation*, Vol. 8, 1979, pp. 141-151.

34. Schrank, D. and T. Lomax. *The 2002 Urban Mobility Report*. 2002.

35. Eisele, W. L., T. J. Lomax, B. J. Gregor and R. D. Arnold. Developing and Implementing Statewide Operations Performance Measures in the State of Oregon: Methodology and Application for Using HERS-ST and Archived Real-Time Data. *Transportation Research Board 84th Annual Meeting*, 2005.

36. Taylor, W. C. and A. S. Abdel-Rahim. *Analysis of Corridor Delay under SCATS Control*. Michigan State University, 1998.

37. Peters, J. M., C. M. Monsere, H. Li, M. Mahmud and S. Boice. Field-Based Evaluation of Corridor Performance after Deployment of an Adaptive Signal Control Systems in Gresham, Oregon. *Transportation Research Board 2008 Annual Meeting CD-Rom*, 2008.

38. Hunter, M. P., S. K. Wu and H. K. Kim *Cobb County ATMS Phase III Evaluation*. Cobb County, Georgia, 2005.

39. Martin, P. T. and A. Stevanovic. *Adaptive Signal Control V, SCATS Evaluation in Park City, Utah*. 2008.

40. Andrews, C. M., S. M. Elahi and J. E. Clark. Evaluation of New Jersey Route 18 OPAC/MIST Traffic Control System. *Transportation Research Record*, Vol. 1603, 1997, pp. 150-155.

41. Hamilton, B. A. *Integrated Corridor Traffic Management Final Evaluation Report*. Minnesota Department of Transportation, 2000.

42. Ghaman, R. S. *ACS-Lite FHWA Adaptive Signal Control Systems*. FHWA, Washington D.C., 2008.

43. Eghtedari, A. G. Measuring the Benefit of Adaptive Traffic Signal Control : Case Study Of Mill Plain Blvd. Vancouver, Washington. *Transportation Research Board 2006 Annual Meeting CD-Rom*, 2006.

44. James E. Moore, I., S. P. Mattingly, C. A. Maccarley and M. G. Mcnally. Anaheim Advanced Traffic Control System Field Operations Test: A Technical Evaluation of SCOOT. *Transportation Planning and Technology*, Vol. 28, No. 6, 2005, pp. 465-482.

45. SRF Consulting Group, Inc. *AUSCI Adaptive Urban Signal Control and Integration*. Minnesota Department of Transportation, 2000.

46. Hunter, M. P., S. K. Wu and H. K. Kim. Practical Procedure to Collect Arterial Travel Time Data Using GPS-Instrumented Test Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1978, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 160-168.

47. *Highway Capacity Manual 2000*. TRB, National Research Council, Washington, D.C., 2000.

48. Logsdon, T. *Understanding the Navstar: GPS, GIS, and IVHS*. Van Nostrand Reinhold, New York, 1995.

49. Taylor, M. A. P., J. E. Woolley and R. Zito. Integration of the Global Positioning System and Geographical Information Systems for Traffic Congestion Studies. *Transportation Research Part C*, Vol. 8, 2000, pp. 257-285.

50. Turner, S. M., W. L. Eisele, R. J. Benz and D. J. Holdener. *Travel Time Data Collection Handbook*. FHWA-PL-98-035. 1998.

51. Quiroga., C. A. and D. Bullock. Measuring Control Delay at Signalized Intersections. *Journal of Transportation Engineering*, Vol. 125, No. 4, 1999, pp. 271-280.

52. Turner, S. M. Advanced Techniques for Travel Time Data Collection. *Transportation Research Record*, Vol. 1551, 1996, pp. 51-58.

53. Czerniak, R. J. *Nchrp Synthesis 301: Collecting, Processing, and Integrating GPS Data into GIS*. Transportation Research Board, National Research Council, Washington, DC, 2002.

54. Ogle, J., R. Guensler, W. Bachman, M. Koutsak and J. Wolf. Accuracy of Global Positioning System for Determining Driver Performance Parameters. *Transportation Research Record*, Vol. 1818, 2002, pp. 12-24.

55. Kim, H. K., S. K. Wu and M. Hunter. A Case Study on Measuring Travel Time, Speed, and Delay Using GPS-Instrumented Test Vehicles. *Proceedings of the Ninth International Conference on Applications of Advanced Technology in Transportation*, 2006, pp. 350-355.

56. *Traffic Engineering Handbook*. Institute of Transportation Engineers, 1999.

57. *A Policy on Design of Highway and Streets*. American Association of State Highway and Transportation Officials, Washington, D.C., 2001.

58. GPS-Explained. www.kowoma.de/en/gps/errors.htm.

59. Wardrop, J. G. Some Theoretical Aspects of Road Traffic Research. *Road Engineering Division Meeting*, Vol. Road Paper No. 36, 1952, pp. 325-379.

60. Herman, R. and T. Lam. Trip Time Characteristics of Journeys to and from Work. *Proceedings of the International Symposium on Transportation and Traffic Theory*, 1974, pp. 57-85.

61. Richardson, A. J. and M. A. P. Taylor. Travel Time Variability on Commuter Journey Time. *High Speed Ground Transportation Journal*, Vol. 12, No. 1, 1978, pp. 75-99.

62. Dandy, G. C. and E. A. McBean. Variability of Individual Travel Time Components. *Journal of transportation*, Vol. 110, No. 3, 1984, pp. 340-356.

63. Sun, C., G. Arr and R. P. Ramachandran. Vehicle Reidentification as Method for Deriving Travel Time and Travel Time Distribution. *Transportation Research Record*, Vol. 1826, 2003, pp. 25-31.

64. Berry, D. S. Evaluation of Techniques for Determining over-All Travel Time. *Proceedings, Highway Research Board, National Research Council*, Vol. 31, 1952, pp. 429-440.

65. Smeed, R. J. and G. O. Jeffcoate. The Variability of Car Journey Times on a Particular Route. *Traffic Engineering & Control*, Vol. 13, No. 6, 1971, pp. 238-243.

66. Hastie, T., R. Tibshirani and J. Friedman *The Elements of Statistical Learning*. Springer, New York, 2001.

67. Kvam, P. H. and B. Vidakovic *Nonparametirc Statistics with Applications to Science and Engineering*. Wiley-Interscience, Hoboken, NJ, 2007.

68. Hines, W., D. Montgomery, D. Goldsman and C. Borror *Probability and Statistics in Engineering, 4th Ed*. John Wiley and Sons, Inc, New York, 2003.

69. *CID Traffic Counts*. Cobb County Department of Transportation, 2004.

70. Therneau, T., E. Atkinson and M. Foundation *An Introduction to Recursive Partitioning Using the RPART Routines*. 1997.

71. Faraway, J. *Extending the Linear Model with R*. Champton & Hall/CRC, Taylor & Francis Group, Boca Raton, 2006.

72. Chang, M. and R. Herman. An Attempt to Characterize Traffic in Metropolitan Areas. *Transportation Science*, Vol. 12, No. 1, 1978, pp. 58-79.

73. Herman, R. and I. Prigogine. A Two-Fluid Approach to Town Traffic. *Science*, Vol. 204, 1979, pp. 148-151.

74. Evans, L., R. Herman and T. Lam. Multivariate Analysis of Traffic Factors Related to Fuel Consumption in Urban Driving. *Transportation Science*, Vol. 10, No. 2, 1976, pp. 205-215.

75. Herman, R. and S. A. Ardekani. Characterizing Traffic Conditions in Urban Areas. *Transportation Science*, Vol. 18, No. 2, 1984, pp. 101-139.

76. Jones, E. G. and W. Farhat. Validation of Two-Fluid Model of Urban Traffic for Arterial Streets. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1876, Transportation Research Board, National Research Council, Washington, D.C., 2004, pp. 132-141.

77. Denney, R. W., J. C. Williams, S. C. S. Bhat and S. A. Ardekani. Calibrating NETSIM for a CBD Using the Two Fluid Model. *Proceedings of the Advanced Traffic Management Conference*, 1993, pp. 169-184.

78. Williams, J. C., H. S. Mahmassani and R. Herman. Analysis of Traffic Network Flow Relations and Two-Fluid Model Parameter Sensitivity. *Transportation Research Record*, Vol. 1005, Transportation Research Board, National Research Council, Washington D.C., 1985, pp. 95-106.

79. Chang, M. and R. Herman. Trip Time Versus Stop Time and Fuel Consumption Characteristics in Cities. *Transportation Science*, Vol. 15, No. 3, 1981, pp. 183-209.

80. Vo, P. T., S. P. Mattingly, S. Ardekani and Y. Dilshad. Comparison of Qality of Service in Two Central Business Districts, Two-Fluid Model Approach. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1999, 2007, pp. 180-188.

81. Mahmassani, H. S., J. C. Williams and R. Herman. Investigation of Network-Level Traffic Flow Relationship: Some Simulation Results. *Transportation Research Record*, Vol. 971, 1984, pp. 121-130.

82. Herman, R., L. A. Malakhoff and S. A. Ardekani. Trip Time-Stop Time Studies of Extreme Driver Behaviors. *Transportation Research Part A*, Vol. 22, No. 6, 1988, pp. 427-433.

83. Williams, J. C., H. S. Mahmassani and R. Herman. Sampling Strategies for Two-Fluid Model Parameter Estimation in Urban Networks. *Transportation Research Part A*, Vol. 29A, No. 3, 1995, pp. 229-244.